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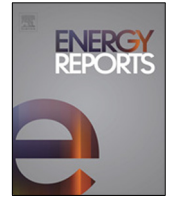
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Review article

Energy management for user's thermal and power needs: A survey

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ABSTRACT

The increasing world energy consumption, the diversity in energy sources, and the pressing environmental goals have made the energy supply–demand balance a major challenge. Additionally, as reducing energy costs is a crucial target in the short term, while sustainability is essential in the long term, the challenge is twofold and contains clashing goals. A more sustainable system and end-users' behavior can be promoted by offering economic incentives to manage energy use, while saving on energy bills. In this paper, we survey the state-of-the-art in energy management systems for operation scheduling of distributed energy resources and satisfying end-user's electrical and thermal demands. We address questions such as: how can the energy management problem be formulated? Which are the most common optimization methods and how to deal with forecast uncertainties? Quantitatively, what kind of improvements can be obtained? We provide a novel overview of concepts, models, techniques, and potential economic and emission savings to enhance energy management systems design.

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1. Introduction

Since 1990, world energy consumption has increased by 58% (Enerdata, 2018), raising concerns over supply, depletion of primary resources, and environmental impact. Society has become aware of the strong correlation between energy consumption and climate change (Akhmat et al., 2014; IEA, 2015), as the energy sector is responsible of roughly two-thirds of all greenhouse-gas emissions related to human activities (IEA, 2015). In 2016, residential and commercial sectors, which include the largest part of buildings, consumed about 40% of total U.S. and Europe energy consumption (U.S. Energy Information Administration, 2018; European Commission, 2019), where buildings are responsible for 36% of carbon dioxide (CO₂) emissions.

The expansion of the energy production capacity requires long-lasting and expensive procedures that have to overcome several difficulties from both a technical and social point of view. With the increasing amount of medium and small scale RES, the transmission and distribution systems have to be adapted to cope with decentralized and fluctuating supply (Pagani et al., 2011). On the one hand, the construction of new overhead lines faces strong opposition (Eddy, 2014; Eto, 2016); on the other hand, although large-scale storage systems mainly in the form of electrochemical batteries have great potential (Fiorini et al., 2018), their costs and performances need to be further enhanced to significantly improved the flexibility of energy system with high penetration of RES (Verzijlbergh et al., 2017). Coal-fired plants have low generation costs (Agora Energiewende, 2014), but high CO₂ emissions; the best hydropower sites – the cleanest way of producing electricity – have been largely already exploited (IRENA, 2012); nuclear power – the second lowest-carbon source for electricity (IEA, 2015) – is under constant societal scrutiny for the effects of possible major failures. Within

this complex scenario, the DRPs promote the shifting in time of load demand by means of economic incentives and time-varying electricity tariffs, leading to operation optimization and economic benefits for the utilities (Siano, 2014; Verzijlbergh et al., 2017). End-users benefit by potentially reducing their energy bills by modifying their consumption patterns. With DRPs utilities limit the risk of bottlenecks along power lines and postpone expensive investments in the infrastructure (U.S. Department of Energy, 2006).

However, a trade-off between automation and user decisions needs to be found. On the one hand, high level of (perceived) control can increase the system acceptability and adoption by its users (Leijten et al., 2014); on the other hand, too many options and alternatives may result in frustration and decision avoidance (Schwartz et al., 2002).

An energy management system (EMS) monitors, meters, and controls energy consumption and production of a building, while adjusting equipment usage by means of scheduling algorithms. The operation scheduling problem consists in planning the use of available resources, such as generators and storage, as well as flexible loads, with the aim of minimizing operation costs and/or the environmental impact, while satisfying the energy demand based on systems' signals such as price. This optimization is often achieved with a two-steps process: first, prediction of prices, production, and consumption are used to determine an optimal scheduling for the future; then, the real-time optimal operation is adjusted according to data coming from the market (price signals), the grid (e.g., overloading), and resources (outputs and demand). Nowadays, the implementation and operation of EMSs is made possible by the growing amount of Internet of Things (IoT) devices and the newest big data techniques available to deal with huge amounts of data. The adoption of EMSs enables efficiency improvements, economic benefits for both end-users and utilities, and reduces the environmental impact of the energy

sector at all scales, from homes to large buildings to groups of buildings (Kopshoff, 2018; Daisyme, 2018).

The energy management concept includes several aspects, such as smart meters (Kádár and Varga, 2012; Depuru et al., 2011), communication and control network (Güngör et al., 2011; Kailas et al., 2012), and schedulers (Georgievski et al., 2012). The scheduler is the component that has to find a solution to the scheduling problem. There are several surveys available in the literature on this topic; for instance, on modeling and on the complexity of home energy management systems (Beaudin and Zareipour, 2015; Vega et al., 2015), on energy management techniques (Gamarra and Guerrero, 2015; Olatomiwa et al., 2016), on distributed energy resources (DERs) operation and control (Baños et al., 2011; Theo et al., 2017; Rahman et al., 2015), on intelligent buildings (Nguyen and Aiello, 2013), and on energy saving (Lee and Cheng, 2016). However, to the best of our knowledge, a review on the operation scheduling problem at the building level is missing. The aim of the present work is to systematize the concepts, models, and optimization techniques of EMSs to help the understanding and, in turn, the design of such systems. We survey the state-of-the-art in energy management for operation scheduling of DERs and end-user's electrical and thermal demand thus allowing us to identify general principles and elaborate novel perspectives for EMSs in residential and office buildings. These are useful guidelines for EMS designers as well as researchers and graduate students investigating new approaches and methods for energy management.

The remainder of the paper is organized as follows. Section 2 introduces methods and criteria used to select and compare the studies. A definition of EMS and the main aggregation concepts are discussed in Section 3. Section 4 offers a comparison of several studies on how the optimal scheduling problem is formulated and modeled. In particular, we discuss the economic frameworks, the load models, and different approaches to information uncertainty. Moreover, we describe the different components of the system (generators, loads, and infrastructure) and their interconnections. Section 5 presents the main optimization techniques applied to the scheduling problem, including modeling for uncertainties. The potential economic and environmental achievements enabled by the development of EMSs are summarized in Section 6. Other surveys on energy management are briefly reviewed in Section 7. An overview of the outcomes and of the possible limitations of this work are discussed in Section 8, while conclusions are drawn in Section 9.

2. Criteria and methods

Optimal operation scheduling in energy systems is a popular and broad topic. It ranges from whole national generation park to a small portion of the distribution grid or even a single household. The operation scheduling is often the last step of larger optimal planning problem, which can include energy generation mix selection, sizing of components, source siting, and, finally, system scheduling. The energy consumptions to be satisfied can be industrial, manufacturing, military, institutional, or domestic. In addition, the scheduling problem can focus only on the electricity demand or also on the thermal one, including hot water, space heating, and cooling. We follow the guidelines as proposed by Kitchenham in Kitchenham (2004) for systematic literature reviews in software engineering. The main steps of the systematic literature review method are presented in the following sections.

2.1. Research questions

Our review focuses on the operation scheduling approaches, addressing the following questions:

- RQ1 : How to formulate the energy management problem?;
- RQ2 : Which are the most common system models, such as DERs, loads, and infrastructure?
- RQ3 : Which are the most common optimization methods?
- RQ4 : How to deal with forecast uncertainties?

To address RQ1, we propose a general definition of the operation scheduling problem and we investigate the main objective functions and economic models used to reach a (near-) optimal resource scheduling solution. As for RQ2, several features are considered to describe the different models, such as DER types, load models, and connections with main grids. Main methods and techniques used for scheduling optimization are surveyed in order to address RQ3 and RQ4. Additionally, we briefly discuss the economic and environmental potential achievements.

2.2. Search keywords

A preliminary search has been carried out using the search engine Google Scholar, and the following keywords: “optimization”, “operation”, “energy management”, “heat and power” or “thermal and electrical”, “building” or “virtual power plants” or “energy hub” or “distributed energy system” or “microgrid”, “end-user” or “consumer”. The selected terms should indicate the main scope of the studies, the considered energy demands to be optimized, the system models and their key elements, and the level of optimization, i.e., the low-voltage distribution grid and end-users. Moreover, only studies published in or after 2010 are considered, in order to focus on the most recent technologies and approaches.

2.3. Inclusion criteria

The initial number of retrieved documents amounted to around 3.790 publications. We then restrict the relevant papers by applying the following inclusion criteria, obtaining a total of 69:

- only English-written peer-reviewed articles published in journals, chapters of periodicals, and proceedings of conferences are included;
- optimal scheduling of available resources is the main objective; studies that focus primarily on optimal design, siting, and sizing of systems are not included;
- either residential or office buildings are the object of the optimization model; industrial, manufacturing, or military facilities are excluded, as are hotels or hospitals; and
- both power and thermal demand have to be explicitly included in the model, so as to have a complete view of the energy consumptions and costs. The thermal demand may include space heating, space cooling, and/or hot water demand.

2.4. Data collection and analysis

From each study, we extract the following information:

- mathematical formulation of the scheduling problem and the objective function(s) to be addressed;
- details of the economic model (e.g., price and costs structure, as well as incentives);
- resources included in the system model;
- optimization techniques; and
- potential economic and environmental savings.

The data is organized in tables and figures in order to easily compare the various models and approaches, in turn to answer the research questions.

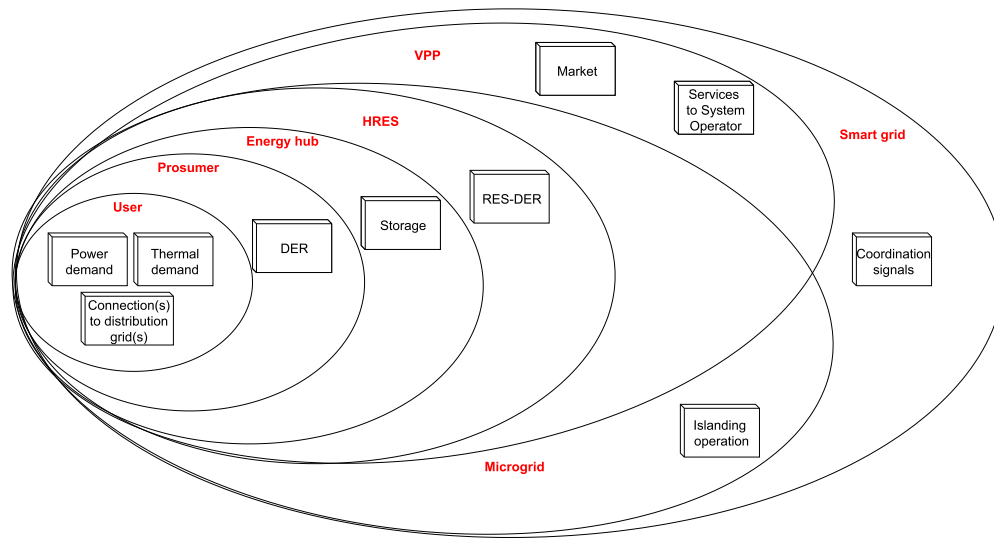


Fig. 1. Aggregation levels of multi-energy systems: the Venn diagram summarizes the minimum requirements in terms of elements that are usually included in the models.

3. Energy management: Main concepts

An EMS coordinates the energy demand and supply between the dispatchable generation units and the loads, while aiming at the fulfillment of economic and environmental objectives. The coordination can be implemented at various levels, from single household to larger portions of the grid, which grow in complexity and in interconnections among DERs and the grid. This is exemplified in Fig. 1, showing the main elements that are usually included in the different aggregation levels that we further discuss in the following sections.

The inner circle of the Venn diagram of Fig. 1 corresponds to the traditional users, who are consumers of thermal and electrical distributed powers. If the user locally produces electricity by means of DERs, such as a combined heat and power (CHP) system, then he is a “prosumer”, and he can feed the surplus of power he does not use into the grid. In Fig. 1, we show that a prosumer is one that is equipped with a DER technology, without specifying its nature. By doing so, we keep the definition of prosumer as general as possible; for instance, both a household with a rooftop solar panel and a building with a gas-burning CHP belongs to the prosumer level. The third level refers to the energy hub model, which usually includes electric and thermal storage devices between generation units and loads. All systems that feature renewable DERs can be included in the set of hybrid renewable energy system (HRES), irrespective of their complexity. A Virtual Power Plant (VPP) is an aggregation of DERs which offers services to the system operators and acts as a single entity on the market. Somehow in contrast with the VPP, a microgrid (MG) has usually the characteristic of being suitable for islanding operation, that means, managing its internal consumptions and supplies without being necessarily connected to the main grid. Finally, the Smart Grid level generalizes all previous models and requires some kind of coordination signals to control and handle sensors, services, and appliances.

All systems that include several sectors of the energy system, such as electricity, heat and cooling, transport, and fuel supply, can be referred to as multi-energy system (MES). According to Mancarella (2014), a MES can range from the size of a building up to entire countries, as long as it integrates different energy vectors for the supply of multiple energy services. Moreover, key elements of the MES concept are the interactions with the external world and among different energy networks. Given that

the present literature review focuses on studies that include both power and thermal demands, the multiplicity of services and sources is basically part of all reviewed papers. Therefore, we can somehow consider all the aggregation levels represented in Fig. 1 as a particular case of MES. A single prosumer connected to both electricity and natural gas grids and equipped with a combined cooling heat and power (CCHP) system to produce electricity, heat, and cooling can already be considered an atomic MES. A multi-energy hub is a MES characterized by an input–output model, while a multi-energy VPP is a MES with a particular attention on balancing services.

As shown in Table 1, the majority of the papers uses the prosumer model, followed by the MG one, and the energy hub representation. Detailed definitions of EMSs and the aggregation levels are available in Appendix A.

4. Operation scheduling

4.1. Problem formulation

Operation scheduling is the planning of available resources, such as generators and storage, with the aim of minimizing operational costs and/or environmental impact in terms of emissions, while covering the energy demand. Where loads are shiftable or curtailable, they become part of the resources to be optimally planned. In order to generalize the operation scheduling problem within the energy context, we propose a general definition for the planning of energy resources to satisfy the load demand, while being independent from the chosen model and objective functions.

Generally speaking, a scheduling problem consists of the allocation of resources to a set of requests over time. Formally, given a set D of requests to satisfy, a set K of resource types, and a discrete representation of time T : a time-discrete scheduling of typed resources to satisfy requests is a mapping

$$s : D \times T \rightarrow K \times \mathbb{R},$$

which associates to each request $d \in D$ and each time step $t \in T$ the type and quantity of resource(s) required to satisfy the request.

The *scheduling problem* consists of a set of variables X ; a set of domain values $V = \{D, T, K, \mathbb{R}\}$ such that $x \in V$; a set of constraints C that restricts the values that the variables can take.

Table 1
Aggregation level.

Aggregation level	Works	# of works
User	Fiorini and Aiello (2018) and Perez et al. (2016)	2
Prosumer	Aki et al. (2016), Alahäivälä et al. (2015), Brandoni et al. (2014), Miyazato et al. (2016), Shaneb et al. (2012), Ashouri et al. (2016), Zhao et al. (2013), Kolen et al. (2017), Elkazaz et al. (2016), Good and Mancarella (2017), Jiang et al. (2017), Kneiske et al. (2018), Larsen et al. (2014), Lorestani et al. (2016), Mauser et al. (2016), Mauser et al. (2015), Braun et al. (2016), Mohsenzadeh and Pang (2018), Qayyum et al. (2015), Razmara et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013) and De Angelis et al. (2013)	29
Energy hub	Brahman et al. (2015), Majidi et al. (2017b), Alipour et al. (2017), Batić et al. (2016), Ha et al. (2017), Huo et al. (2018), Javadi et al. (2017), Ma et al. (2017), Neyestani et al. (2015), Qi et al. (2017), Rayati et al. (2015), Setlhaolo et al. (2017), Sheikhi et al. (2015) and Skarvelis-Kazakos et al. (2016)*	14
Hybrid renewable energy system	Nojavan et al. (2017), Majidi et al. (2017a), Dagdougui et al. (2012) and Rouholamini and Mohammadian (2015)	4
Microgrid	Skarvelis-Kazakos et al. (2016)* Holjevac et al. (2015), Alipour et al. (2015), Mao et al. (2010), Safamehr and Rahimi-Kian (2015), Prinsloo et al. (2016), Tabar et al. (2017), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Parisio et al. (2015), Parisio et al. (2017), Rodriguez-diaz et al. (2017) and Zhang et al. (2015)	20
Virtual power plant	Skarvelis-Kazakos et al. (2016)* and Brenna et al. (2015)	2
Total		71

Three aggregation levels are interconnected in Skarvelis-Kazakos et al. (2016).

In particular, a constraint c_j over a subset of variables $X_j \subset X$ is a relation $R_j(X_j)$ on the corresponding subset of domains $V_j \subset V$.

A *feasible solution* to a scheduling problem is an assignment to each variable in X such that every constraint in C is satisfied. We denote the set of all feasible solutions to a scheduling problem as I . A cost function f is a mapping $f : I \rightarrow \mathbb{R}$, that associates with each feasible solution $i \in I$ a cost value. The optimal cost function f_{opt} of a scheduling instance is defined by $f_{\text{opt}} = \min\{f(i) | i \in I\}$ and the set of optimal solutions to a scheduling problem is denoted by $I_{\text{opt}} = \{i \in I | f(i) = f_{\text{opt}}\}$.

Within the energy management context, D is the set of power demands to be satisfied, T is a finite set of ordered time steps, and K is the set of types of available resources, which include distribution grids (e.g., gas, electricity, or heat distribution grids) and DERs (e.g., CHP, photovoltaic (PV), or boiler). A solution to the derived scheduling problem is a set of pairs (type, quantity) of resources that satisfy a power demand $d_i \in D$ at time step $t_j \in T$.

4.2. Objectives

The main objective functions for the optimal operation scheduling problem are: (1) minimization of system operation costs, (2) minimization of consumer's energy bills, (3) maximization of system profit, (4) minimization of emission costs, (5) minimization of reliability costs, (6) minimization of primary energy consumption costs, (7) minimization of emission, (8) minimization of peak demand, (9) minimization of regulation effort, (10) minimization of electricity imported from the grid, (11) minimization of deviation from original demand, (12) maximization of stored energy, (13) minimization of user's discomfort, (14) maximization of efficiency, (15) minimization of switching events, (16) maximization of social surplus, (17) minimization of power imbalance, (18) maximization of load penetration, (19) maximization of PV self-consumption, (20) maximization of utility profit, and (21) maximization of user's satisfaction.

The final scheduling can be sought by optimizing a single-objective (SO) or a multi-objective (MO) problem, and by assuming different perspectives. Table 2 presents an overview of how the scheduling problem can be formulated, distinguishing between SO and MO objective problems. When a multi-agent (MA) approach is taken, each agent aims at one or multiple goals. Moreover, the table indicates the nature of the optimization problem,

while Table 3 summarizes the objective function(s) to be optimized. Objectives may be economic (e.g., minimization of costs), environmental (e.g., minimization of CO₂ emissions), technical (e.g., maximization of system efficiency), or social (e.g., minimization of user's discomfort).

4.2.1. Single-objective

As shown in Table 2, the most common approach is to formulate an economic SO function over a defined time horizon. It is worth noticing that the same objective function can include a wide range of cost components in different studies. For instance, the system profit maximization in Alipour et al. (2015) takes into account costs for buying electricity and fuel, revenues for selling the electricity surplus to the market, and generation units startup and shutdown costs, while Brenna et al. replace the technical costs of generation units with the subsidies for RES and the economic penalties due to load shedding and deviation from the scheduled power exchange (Brenna et al., 2015). The minimization of system operation costs can be straightforwardly defined as the sum of purchased gas and net electricity from the grid (e.g., Ha et al., 2017; Neyestani et al., 2015; Rodriguez-diaz et al., 2017), but also as the sum of import/export priced in the day-ahead and imbalance markets, gas cost, remuneration for offering the reserve service, penalties due to excessive temperature oscillation inside buildings, and due to reactive power supply (Good and Mancarella, 2017). Both the electricity import from and surplus export to the main grid are considered as costs to be minimized in Comodi et al. (2015).

Some studies include into the economic objective function some environment-oriented goals. For instance, the system operation costs to be minimized in Holjevac et al. (2015) and Shaneb et al. (2012), Ma et al. (2017) include energy waste costs and emission costs due to a carbon tax. In Moghaddas Tafreshi et al. (2016), the microgrid manager aims at maximizing the system profit, while taking into account emission costs. Similarly, the minimization costs problem proposed in Kriett and Salani (2012) and Good and Mancarella (2017) includes not only common terms such as fuel and imported electricity costs, but also “social costs”, such as the costs related with degradation of goods inside the refrigerator (Kriett and Salani, 2012), which can be affected by the scheduling of the refrigerator, and the comfort costs due to fluctuations in the heating temperature (Kriett and Salani, 2012; Good and Mancarella, 2017). Other studies translate technical objectives in economic terms; for instance, a battery lifetime cost

Table 2
Classification of scheduling problem.

Formulation	Nature	Works	# of works
Single-objective	Eco	Aki et al. (2016), Alahäivälä et al. (2015), Shaneb et al. (2012), Ashouri et al. (2016), Elkazaz et al. (2016), Good and Mancarella (2017), Jiang et al. (2017), Kneiske et al. (2018), Lorestani et al. (2016), Mauser et al. (2016), Mauser et al. (2015), Mohsenzadeh and Pang (2018), Qayyum et al. (2015), Salpakari and Lund (2016), Salpakari et al. (2017), Severini et al. (2013), Sheikhi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013), De Angelis et al. (2013), Alipour et al. (2017), Batić et al. (2016), Ha et al. (2017), Huo et al. (2018), Javadi et al. (2017), Ma et al. (2017), Neyestani et al. (2015), Qi et al. (2017), Rayati et al. (2015), Sheikhi et al. (2015), Rouholamini and Mohammadian (2015), Holjevac et al. (2015), Alipour et al. (2015), Kriett and Salani (2012), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Moghaddas Tafreshi et al. (2016), Parisio et al. (2015), Parisio et al. (2017), Rodriguez-diaz et al. (2017), Zhang et al. (2015), Brenna et al. (2015), Razmara et al. (2017)* and Skarvelis-Kazakos et al. (2016)*	46
	Tech	Dagdougui et al. (2012), Huo et al. (2018), Javadi et al. (2017), Perez et al. (2016), Qayyum et al. (2015), Salpakari and Lund (2016), Shi et al. (2016), Zhao et al. (2013)*, Kolen et al. (2017)*, Larsen et al. (2014)* and Razmara et al. (2017)*	11
	Env	Holjevac et al. (2015), Shaneb et al. (2012), Ma et al. (2017), Fiorini and Aiello (2018) and Skarvelis-Kazakos et al. (2016)*	5
	Soc	Kriett and Salani (2012), Good and Mancarella (2017) and Sheikhi et al. (2015)	2
	Eco, Env	Mao et al. (2010), Brandoni et al. (2014), Brahman et al. (2015), Prinsloo et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017) and Mohammadi et al. (2017)	9
Multi-objective	Eco, Soc	Miyazato et al. (2016), Anvari-Moghaddam et al. (2015) and Anvari-Moghaddam et al. (2017)*	3
	Eco, Tech	Safamehr and Rahimi-Kian (2015) and Shirazi and Jadid (2015)	2
	Eco, Env, Soc	Setlhaolo et al. (2017)	1
	Eco, Env, Tech, Soc	Braun et al. (2016)	1

An overview of how the operation scheduling problem of DER and demand can be formulated. The optimization problem can be formulated as a single-objective (SO) or multi-objective (MO) problem; works indicated with an * solve a SO or MO problem within a multi-agent framework. The nature of the main objectives can be economic (Eco), environmental (Env), social (Soc), and/or technical (Tech).

Table 3
Objective functions.

Obj. funct.	Works	# of works
(1)	Holjevac et al. (2015), Mao et al. (2010), Brandoni et al. (2014), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Alipour et al. (2017), Shaneb et al. (2012), Rouholamini and Mohammadian (2015), Elkazaz et al. (2016), Good and Mancarella (2017), Ha et al. (2017), Huo et al. (2018), Javadi et al. (2017), Jiang et al. (2017), Kneiske et al. (2018), Ma et al. (2017), Lorestani et al. (2016), Mauser et al. (2016), Mauser et al. (2015), Braun et al. (2016), Neyestani et al. (2015), Qi et al. (2017), Razmara et al. (2017), Salpakari and Lund (2016), Salpakari and Lund (2016), Shirazi and Jadid (2015), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013), De Angelis et al. (2013), Tabar et al. (2017), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Mohammadi et al. (2017), Rodriguez-diaz et al. (2017) and Zhang et al. (2015)	41
(2)	Aki et al. (2016), Alahäivälä et al. (2015), Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Miyazato et al. (2016), Batić et al. (2016), Ashouri et al. (2016), Anvari-Moghaddam et al. (2017), Mohsenzadeh and Pang (2018), Parisio et al. (2015), Parisio et al. (2017), Qayyum et al. (2015), Rayati et al. (2015), Setlhaolo et al. (2017), Severini et al. (2013) and Sheikhi et al. (2016)	16
(3)	Alipour et al. (2015), Brenna et al. (2015) and Moghaddas Tafreshi et al. (2016)	3
(4)	Mao et al. (2010), Brandoni et al. (2014), Rayati et al. (2015), Setlhaolo et al. (2017) and Shaneb et al. (2012)	5
(5)	Mao et al. (2010)	1
(6)	Brandoni et al. (2014)	1
(7)	Brahman et al. (2015), Prinsloo et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017), Fiorini and Aiello (2018), Braun et al. (2016), Mohammadi et al. (2017) and Skarvelis-Kazakos et al. (2016)	10
(8)	Safamehr and Rahimi-Kian (2015), Zhao et al. (2013), Kolen et al. (2017), Perez et al. (2016), Qayyum et al. (2015) and Shirazi and Jadid (2015)	6
(9)	Miyazato et al. (2016)	1
(10)	Dagdougui et al. (2012) and Shi et al. (2016)	2
(11)	Prinsloo et al. (2016) and Dagdougui et al. (2012)	2
(12)	Dagdougui et al. (2012)	1
(13)	Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Braun et al. (2016), Rayati et al. (2015), Setlhaolo et al. (2017) and Sheikhi et al. (2016)	6
(14)	Zhao et al. (2013)	1
(15)	Kolen et al. (2017) and Braun et al. (2016)	2
(16)	Jiang et al. (2017)	1
(17)	Larsen et al. (2014)	1
(18)	Razmara et al. (2017)	1
(19)	Salpakari and Lund (2016)	1
(20)	Sheikhi et al. (2015)	1
(21)	Sheikhi et al. (2015)	1

penalty is part of the system operation costs in [Huo et al. \(2018\)](#) and [Javadi et al. \(2017\)](#), in order to prevent storage degradation and ensure a longer lifetime. In [Rayati et al. \(2015\)](#), the total costs of a residential energy hub include user's bills, discomfort costs due to appliances delay and plug-in electric vehicles (PEVs) storage level, and CO₂ emission costs. Dagdougui et al. propose an energy management model for green buildings based on a

purely technical optimization problem, whose main objectives are the minimization of imported electricity from the distribution grid and of the deviation from the original demand, and the maximization of stored energy ([Dagdougui et al., 2012](#)). A game-theory based approach is taken in [Sheikhi et al. \(2015\)](#), where the payoff function of each prosumer to be maximized includes

energy costs, user's satisfaction, and, at the same time, guarantees the maximization of the electricity utility profit.

4.2.2. Multi-objective

Many studies propose a MO scheduling model, which usually includes two or more objectives, often of different nature. The most common approach is to combine objective functions of economic and environmental nature, for instance minimization of operation costs and pollutant emissions (Nojavan et al., 2017; Majidi et al., 2017a; Mohammadi et al., 2017; Prinsloo et al., 2016; Majidi et al., 2017b), while the authors of Brandoni et al. (2014) include primary energy consumption costs as well. Economic and technical goals are combined in Safamehr and Rahimi-Kian (2015) and Shirazi and Jadid (2015), where DERs and the partially flexible load of a building are scheduled in order to minimize the energy bills, while minimizing the peak demand, aiming to improve the grid operation. An original problem is proposed in Miyazato et al. (2016), where the objective functions have an economic and a social goal, namely the minimization of the electricity bill and of the consumer's regulation effort. The latter is defined as the reduced cost due to the modification of the initial usage plan of flexible electrical appliances, according to real-time pricing. The aim is to minimize the costs of buying power from the main grid, while limiting the user's discomfort due to rescheduling of shiftable appliances. Similarly, the MO problem proposed in Anvari-Moghaddam et al. (2015) aims at minimizing the total operation costs and the user's discomfort, which is due to the deviation from the thermal and electrical comfort zones. In the first case, the inside temperature varies more than 2 °C from the set point; in the latter, residential appliances are scheduled outside the desirable time window. In Braun et al. (2016), smart residential buildings are optimized with respect to four objective functions of different nature, namely total energy costs, CO₂ emissions, thermal discomfort, and technical wear out due to switching HVAC devices on and off. The reader interested in the most common approaches to deal with multi-objective problems is referred to Section 5.1.

4.2.3. Multi-agent

Beside single- and multi-objective problems, some studies propose a multi-agent scheduling problem. In this approach, each agent has its own goal, while resources to be scheduled are shared. The agents may act on the same environment, e.g., the same space where three main energy zones are identified, namely electricity, cooling, and heating zone, as in Zhao et al. (2013), or they can act in different energy systems, while being part of the same cluster, as in Kolen et al. (2017), Anvari-Moghaddam et al. (2017), Larsen et al. (2014), Razmara et al. (2017) and Skarvelis-Kazakos et al. (2016). The idea is to achieve a global objective by coordination and exchange of information among the agents. In Zhao et al. (2013), the ultimate goal is to minimize the energy costs, which is achieved by optimizing the technical objectives of three agents. In particular, the heating agent aims at maximizing the efficiency of the heating system, so that less natural gas has to be burned to produce hot water. Similarly, the cooling agent has to maximize the efficiency of the cooling devices; the electric agent has to reduce the peak electric load and communicate and coordinate the system with the main grid. In Kolen et al. (2017) and Anvari-Moghaddam et al. (2017), the optimization problem is divided into two levels, a local one and a cluster one. In Kolen et al. (2017), each building energy system minimizes the number of switching events of their heating devices, so that efficiency is improved and the stress of each device is reduced. Then, the cluster level minimized the fluctuation of the energy demand, by modifying the number of switching events in each building within a certain range. In Anvari-Moghaddam

et al. (2017), each residential end-user corresponds to a building management agent, which aims at scheduling its appliances by finding a trade-off between minimizing the energy costs and the electrical and thermal discomfort levels. At a higher level, a centralized agent coordinates all MG agents, which include also RES agents, monitoring wind turbine (WT) and PV, and a battery bank agent. The goal of the EMS proposed by Larsen et al. is to operate CHP systems to minimize the overall power imbalance of a network which consists in a group of interconnected households (Larsen et al., 2014). The global objective is achieved while each agent aims at minimizing the local power imbalance, defined as the weighted sum of the changes in energy productions and in power demand between two consecutive time steps, and a share of the imbalance information of the neighbor agents. In Razmara et al. (2017), a building controller aims at minimizing the electricity costs, while satisfying the non-dispatchable loads and managing the flexible ones. The resulting load profile is then sent to a distribution grid controller, which runs a power flow analysis to check the feasibility of the load profile in terms of maximum allowable load. If there is any infeasibility, the grid controller sends a feedback with the maximum allowable load to the building controller, and the load profile has to be adjusted accordingly.

4.2.4. Centralized vs decentralized control

One of the key aspects of the optimal scheduling is the perspective from which the problem is formulated. As represented in Fig. 2, a central EMS is assumed to have all the informations about the current state of the entire system and it is in charge of its optimal operation, according to the different objectives (Section 4.2). Irrespective of the used aggregation level (see Table 1), the size of the centrally controlled system can greatly vary, from a single household or office, (e.g., Alahäivälä et al., 2015; Ashouri et al., 2016; Brahman et al., 2015; Dagdougui et al., 2012; Kriett and Salani, 2012; Lorestani et al., 2016; Braun et al., 2016; Fiorini and Aiello, 2018; Mauser et al., 2015, 2016; Miyazato et al., 2016; Shaneb et al., 2012; Qayyum et al., 2015; Salpakari and Lund, 2016; Setlhaolo et al., 2017; Shirazi and Jadid, 2015; Shi et al., 2016; Shirazi and Jadid, 2017; Zhang et al., 2015; De Angelis et al., 2013), to a building composed by multiple offices (Safamehr and Rahimi-Kian, 2015) or apartments (e.g., Brandoni et al., 2014; Farmani et al., 2018; Comodi et al., 2015; Zhang et al., 2013), to a larger community with several loads and DERs (e.g., Alipour et al., 2015; Anvari-Moghaddam et al., 2015; Batić et al., 2016; Brenna et al., 2015; Elkazaz et al., 2016; Good and Mancarella, 2017; Ha et al., 2017; Holjevac et al., 2015; Huber et al., 2013; Huo et al., 2018; Moghaddas Tafreshi et al., 2016; Mohammadi et al., 2017; Alipour et al., 2017; Ma et al., 2017; Javadi et al., 2017; Mahoor et al., 2013; Majidi et al., 2017a,b; Mao et al., 2010; Nojavan et al., 2017; Prinsloo et al., 2016; Rouholamini and Mohammadian, 2015; Tabar et al., 2017; Mohsenzadeh and Pang, 2018; Neyestani et al., 2015; Parisio et al., 2015; Perez et al., 2016; Qi et al., 2017; Salpakari et al., 2017).

Some studies (Kneiske et al., 2018; Rayati et al., 2015; Sheikhhi et al., 2016) combine a centralized EMS with a low-level distributed one, which is implemented directly on the components of the system, e.g., thermal and electrical storages, loads, generation DERs, and PEVs. In Severini et al. (2013), the energy management of a household is divided into two tasks which are performed sequentially. First, the minimal energy to provide the heat pump with is calculated, taking into account the nonlinear thermal dynamics of the system; next, the optimal scheduling of appliances and storage are determined, given the results of the first optimization as input.

A decentralized control is implemented in Aki et al. (2016), where each dwelling has its own EMS, and it can collaborate with

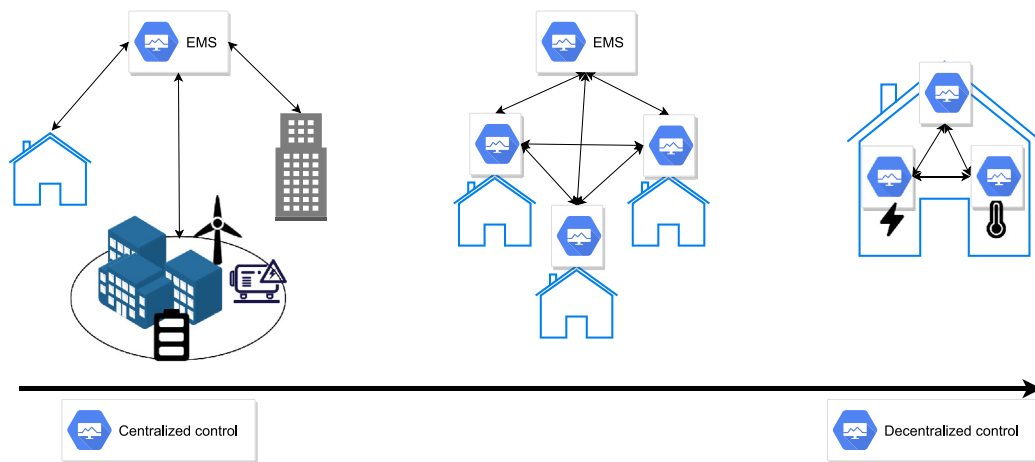


Fig. 2. Centralized vs decentralized control: from a central EMS that has perfect knowledge of the current state of the entire system (e.g., a single household, a building, or a larger community), to several decentralized EMSs for different energy areas or devices. When several EMSs are involved in the optimal scheduling, they may collaborate and/or be coordinated by a global one.

the others and the main grid by exchanging electricity and hot water. In other studies, residential units control their own electric appliances and/or heating system finding the optimal scheduling of all devices. The resulting scheduling may be later adjusted by a global controller (Kolen et al., 2017; Parisio et al., 2017; Razmara et al., 2017), or it may be taken as input to centrally coordinate other systems, such as a battery bank (Anvari-Moghaddam et al., 2017) or the electricity market (Jiang et al., 2017; Sheikhi et al., 2015). In Larsen et al. (2014), the decentralized control receives information from neighbor households, so that local decisions contribute to a common goal, such as the real-time balance of supply and demand at network level. In Skarvelis-Kazakos et al. (2016), a hierarchical structure is proposed, such that the low-level agents control the devices, forecasting their demand or production, and knowing their parameters. The optimization of energy import is done by another agent, whose optimal solution has to be validated by a technical agent, based on technical grid constraints. Last, the commercial trades are set by a commercial agent, according to the market scenario. If grid or market constraints are violated or modified, then the optimal scheduling has to be adjusted. A fully decentralized control is proposed within a single prosumer in Zhao et al. (2013), where three EMSs, called agents, control three energy zones and, at the same time, are coordinated among themselves and the external grid by one of the agent.

4.3. Economic model

The economic model is a key aspect of the scheduling problem, especially when the main goals are economic. Hourly varying prices may enable cost savings by shifting appliances in time, while a constant tariff is usually known in advance, but it is not flexible. An overview of different economic approaches is drawn in the following sections and summarized in Table 4.

4.3.1. Electricity price

To take account of price variability, one has to set a time interval. Several studies use a 20-minutes (Miyazato et al., 2016), half-hourly (Holjevac et al., 2015; Razmara et al., 2017; Shirazi and Jadid, 2015, 2017; Zhang et al., 2013, 2015), or hourly variable intervals (Alahäivälä et al., 2015; Alipour et al., 2015; Brandoni et al., 2014; Majidi et al., 2017b; Alipour et al., 2017; Kriett and Salani, 2012; Rouholamini and Mohammadian, 2015; Anvari-Moghaddam et al., 2015, 2017; Huo et al., 2018; Jiang et al., 2017; Ma et al., 2017; Moghaddas Tafreshi et al., 2016; Parisio

et al., 2015, 2017; Rodriguez-diaz et al., 2017; Salpakari and Lund, 2016; Salpakari et al., 2017; Severini et al., 2013; Sheikhi et al., 2015; De Angelis et al., 2013). According to a popular tariff scheme, many studies distinguish two or more price levels based on the time-of-use of power, namely, off-peak, mid-peak, and on-peak hours. Few authors, on the other hand, consider fix constant prices for both purchasing and selling electricity.

The economic model used in Nojavan et al. (2017) and Majidi et al. (2017a) includes a monthly lump-sum, irrespective of the imported energy; in Batić et al. (2016) a one-time variable fee is charged according to the maximum imported power over the selected temporal horizon. In Shirazi and Jadid (2015), Shirazi and Jadid (2017), Zhang et al. (2013) and Zhang et al. (2015), when the residential prosumer imports from or exports to the grid more than an agreed threshold, she is charge with an extra cost on top of the usual price.

The majority of studies take into account the possibility of buy-back, that is, selling locally generated electricity in excess to the main distribution grid. The selling price can be lower than the purchasing price, being affected by overhead costs, such as tax and distribution grid quota (e.g., Holjevac et al., 2015; Alahäivälä et al., 2015; Mao et al., 2010; Brandoni et al., 2014; Safamehr and Rahimi-Kian, 2015; Tabar et al., 2017; Shaneb et al., 2012; Rouholamini and Mohammadian, 2015; Elkazaz et al., 2016; Kneiske et al., 2018; Mauser et al., 2016, 2015; Moghaddas Tafreshi et al., 2016; Salpakari and Lund, 2016; Salpakari et al., 2017; Severini et al., 2013; Zhang et al., 2013, 2015; De Angelis et al., 2013), or they can be equal (e.g., Aki et al., 2016; Alipour et al., 2015; Brahman et al., 2015; Miyazato et al., 2016; Kriett and Salani, 2012; Anvari-Moghaddam et al., 2015, 2017; Javadi et al., 2017; Jiang et al., 2017; Ma et al., 2017; Qi et al., 2017; Rayati et al., 2015; Shirazi and Jadid, 2015, 2017). In Nojavan et al. (2017) and Ashouri et al. (2016), the price for selling solar power is higher or lower than the purchasing price depending on the current season or the applied tariff policy, respectively. According to Serbian and Ontario regulations, export price is significantly higher than import price in Batić et al. (2016) and Qayyum et al. (2015), respectively. As a result, all locally renewable power is sold to the main grid. In Mohsenzadeh and Pang (2018), nodal selling and purchasing prices are determined based on a three-level time-of-use tariff, by allocating power losses to each node. Such losses depend on the load level and the location of the node within the grid.

Table 4
Economic model.

Power			
Tariff	(semi-)Hourly	Miyazato et al. (2016), Holjevac et al. (2015), Alahäivälä et al. (2015), Alipour et al. (2015), Brandoni et al. (2014), Majidi et al. (2017b), Alipour et al. (2017), Kriett and Salani (2012), Rouholamini and Mohammadian (2015), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Brenna et al. (2015), Farmani et al. (2018), Good and Mancarella (2017), Huo et al. (2018), Jiang et al. (2017), Ma et al. (2017), Moghaddas Tafreshi et al. (2016), Parisio et al. (2015), Parisio et al. (2017), Razmara et al. (2017), Rodriguez-diaz et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Severini et al. (2013), Sheikhi et al. (2015), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013), Zhang et al. (2015) and De Angelis et al. (2013)	32
	Time-of-use	Aki et al. (2016), Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017), Batić et al. (2016), Ashouri et al. (2016), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Ha et al. (2017), Huo et al. (2018), Lorestani et al. (2016), Mahoor et al. (2013), Mohsenzadeh and Pang (2018), Neyestani et al. (2015), Qayyum et al. (2015), Qi et al. (2017), Rayati et al. (2015), Setlhaolo et al. (2017) and Severini et al. (2013)	23
	Constant	Mao et al. (2010), Shaneb et al. (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Elkazaz et al. (2016), Huber et al. (2013), Javadi et al. (2017), Kneiske et al. (2018), Mauser et al. (2016), Mauser et al. (2015), Mohammadi et al. (2017) and Skarvelis-Kazakos et al. (2016)	12
	Lump-sum	Nojavan et al. (2017), Majidi et al. (2017a) and Batić et al. (2016)	3
	Threshold-based charge	Shirazi and Jadid (2015), Shirazi and Jadid (2017), Zhang et al. (2013) and Zhang et al. (2015)	4
Fuel			
Tariff	Constant	Mao et al. (2010), Alahäivälä et al. (2015), Holjevac et al. (2015), Aki et al. (2016), Brandoni et al. (2014), Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Tabar et al. (2017), Alipour et al. (2017), Shaneb et al. (2012), Prinsloo et al. (2016), Batić et al. (2016), Ashouri et al. (2016), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Farmani et al. (2018), Elkazaz et al. (2016), Good and Mancarella (2017), Ha et al. (2017), Huber et al. (2013), Huo et al. (2018), Javadi et al. (2017), Jiang et al. (2017), Kneiske et al. (2018), Ma et al. (2017), Mahoor et al. (2013), Mauser et al. (2016), Mauser et al. (2015), Braun et al. (2016), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Neyestani et al. (2015), Parisio et al. (2015), Parisio et al. (2017), Rayati et al. (2015), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013) and Zhang et al. (2015)	42
	Two-part	Nojavan et al. (2017) and Majidi et al. (2017a)	2
	Daily	Salpakari et al. (2017)	1
	(semi-)Hourly	Rodriguez-diaz et al. (2017), Setlhaolo et al. (2017) and Sheikhi et al. (2015)	3

4.3.2. Fuel price

The majority of studies consider a constant fuel price, irrespective of the type of fuel, such as natural gas (Mao et al., 2010; Alahäivälä et al., 2015; Holjevac et al., 2015; Aki et al., 2016; Brandoni et al., 2014; Brahman et al., 2015; Safamehr and Rahimi-Kian, 2015; Tabar et al., 2017; Alipour et al., 2017; Shaneb et al., 2012; Ashouri et al., 2016; Kriett and Salani, 2012; Anvari-Moghaddam et al., 2015; Zhao et al., 2013; Anvari-Moghaddam et al., 2017; Farmani et al., 2018; Elkazaz et al., 2016; Good and Mancarella, 2017; Ha et al., 2017; Huber et al., 2013; Huo et al., 2018; Javadi et al., 2017; Jiang et al., 2017; Kneiske et al., 2018; Ma et al., 2017; Mahoor et al., 2013; Mauser et al., 2016, 2015; Braun et al., 2016; Moghaddas Tafreshi et al., 2016; Neyestani et al., 2015; Parisio et al., 2015, 2017; Rayati et al., 2015; Shirazi and Jadid, 2015; Sheikhi et al., 2016; Shirazi and Jadid, 2017; Skarvelis-Kazakos et al., 2016; Zhang et al., 2013, 2015), liquefied petroleum gas (LPG) (Prinsloo et al., 2016), oil (Batić et al., 2016), or gasoline (Salpakari et al., 2017). A two-part tariff for natural gas is applied in Nojavan et al. (2017) and Majidi et al. (2017a), with a monthly fix fee and a variable one, related with the actual purchases. Hourly gas prices are considered in Rodriguez-diaz et al. (2017), Setlhaolo et al. (2017) and Sheikhi et al. (2015), while daily values are applied in Salpakari et al. (2017), where yearly costs are investigated.

4.3.3. DRP

A DRP is defined by the U.S. Department of Energy (DOE) (U.S. Department of Energy, 2006) as the “changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized”. The goals of DRPs are twofold: on the one hand, the consumers can reduce their energy bills by modifying their normal consumption patterns according to market price variability; on the other hand, the utility can

reduce the risk of bottlenecks along lines, improving the system reliability, and postponing expensive investments in new generation plant and increasing of infrastructure capacity (U.S. Department of Energy, 2006; Siano, 2014). DRPs can be distinguished in dispatchable and non-dispatchable (Shariatzadeh et al., 2015). The former group – often referred to as incentive-based – offers financial reward/penalty schemes to end-users willing to let the system operator reduce, curtail, or interrupt their delivery during periods of local reliability-threatening peak demand or high prices. The second group is based on offering end-users time-varying rates (e.g., real-time pricing, time-of-use tariffs, critical-peak pricing) to motivate them to modify their demand over time while saving money (U.S. Department of Energy, 2006; Siano, 2014; Albadi and El-Saadany, 2007). Given the economic scheme, such DRPs are referred to as price-based. Some recent studies (Neyestani et al., 2015; Fiorini and Aiello, 2018) propose energy-carrier-based DRPs, which give the users the possibility to decide which energy carrier is used for part of the load, based on price signals (Neyestani et al., 2015) or CO₂ signals (Fiorini and Aiello, 2018).

DRPs are included into the optimization problem by several researchers (see Table 6), with the aim of increasing system flexibility, potential cost savings, reducing environmental impact, and flattening out load profile over time (Safamehr and Rahimi-Kian, 2015). Several studies consider shiftable electric load, often limited to specific appliances (e.g., IT equipment (Batić et al., 2016), air conditioning (AC) and domestic appliances (Ashouri et al., 2016; Jiang et al., 2017; Mauser et al., 2016, 2015; Fiorini and Aiello, 2018; Braun et al., 2016; Mohsenzadeh and Pang, 2018; Parisio et al., 2015, 2017; Perez et al., 2016; Qayyum et al., 2015; Qi et al., 2017; Rayati et al., 2015; Salpakari and Lund, 2016; Setlhaolo et al., 2017; Severini et al., 2013; Shirazi and Jadid, 2015; Sheikhi et al., 2016; Shi et al., 2016; Shirazi and Jadid, 2017; Zhang et al., 2013, 2015; De Angelis et al., 2013), electric

heat pump (Good and Mancarella, 2017), and electric vehicle (Salpakari et al., 2017)) or to a fixed amount of the total demand in any time interval (Mahoor et al., 2013). Also electric vehicles can offer a service for power peak shaving, as the charging process can be controlled and shifted in time, if needed (Brenna et al., 2015).

Many studies assume curtailing the electric and thermal load as a viable option for balancing the system, even if no reward is usually offered to end-user for this service. By contrast, in Farmani et al. (2018) and Mohammadi et al. (2017), the utility pays a fare of 0.04\$/kWh and 1.2 times of the electricity price, respectively, to the users for participation in DRPs. The demand involved in curtailing is often the lighting system (Brahman et al., 2015; Braun et al., 2016), as it can be dimmed, as well as the space heating and hot water demand, if a maximum temperature deviation is considered possible (Brahman et al., 2015; Anvari-Moghaddam et al., 2015, 2017; Good and Mancarella, 2017; Braun et al., 2016; Mohsenzadeh and Pang, 2018; Parisio et al., 2015, 2017; Qi et al., 2017; Razmara et al., 2017; Salpakari et al., 2017; Setlhaolo et al., 2017; Severini et al., 2013; Shirazi and Jadid, 2015, 2017; Zhang et al., 2015; De Angelis et al., 2013). Variation in heating demand is interpreted as a procedure of pre-heating (Batić et al., 2016) or pre-cooling (Perez et al., 2016), where a maximum deviation of a couple of degrees from the desired temperature is allowed.

4.3.4. RES incentives and emission costs

Along with electricity and fuel prices, there might be other economic factors influencing the total production and operation costs of a system, such as incentives for renewable production and emission penalties. Possible revenues for the prosumer come not only from the electricity sold to the grid via feed-in tariff schemes, but also from support mechanisms for the power produced by small-scale DER devices (Brandoni et al., 2014; Shaneb et al., 2012; Brenna et al., 2015) and from the Tradable White Certificates for supporting CHP production (Brandoni et al., 2014). Moreover, according to national schemes for supporting CHP and solar production, in Brandoni et al. (2014) and Kneiske et al. (2018) part of the fuel costs for the CHP unit are subjected to a tax rebate.

Regarding the emission costs, a fix cost €/tonCO₂ is considered in Brandoni et al. (2014), Shaneb et al. (2012), Rayati et al. (2015) and Setlhaolo et al. (2017), as well as in Mao et al. (2010) and Moghaddas Tafreshi et al. (2016), although the latter studies do not specify which emitted pollutants are included in the model.

4.4. Distributed energy resources

“Distributed Energy Resources” (DER) is a broad term that can include all resources generating electricity (Rahman et al., 2015) and/or heat near the point of use at distribution levels, mainly with the aim of achieving energy cost savings and emission lowering, while reducing transmission congestions and energy losses.

Following the classification suggested in Eid et al. (2016), DERs can be distinguished according to their role within the system, i.e., generation, transformation, and storage. The most common DERs are summarized in Table 5 and their interconnections are outlined in Fig. 3. The triangles are the sources, either dispatchable (on the left) or non-dispatchable ones (on the right), and electricity and/or heat are produced via generation DERs (hexagons). Transformation DERs (trapezoids) take electricity as input to satisfy the thermal load, which includes both heating and cooling. Both electric and thermal storage devices are represented by cylinders and connected to the system by bi-directional flows.

4.4.1. Generation

Generation resources produce electricity and/or heat from primary energy sources (e.g., fossil fuels, solar or wind energy). They are dispatchable, if their output can be controlled and adjusted, or non-dispatchable, if their output is not adjustable (Rahman et al., 2015). The most common ones are included in Fig. 3 within hexagons.

Dispatchable generating DERs include all controllable generation systems that can be turned on or off and whose output can be adjusted on demand, such as gas turbines (GTs), micro turbines (MTs), fuel cells (FCs), internal combustion engine (ICE), hydro, CHP systems, boilers, Stirling engine, etc. Prinsloo et al. (2016) FCs produce electricity and heat, by burning natural gas (e.g., Shaneb et al., 2012; Nojavan et al., 2017; Aki et al., 2016; Anvari-Moghaddam et al., 2015) or hydrogen (e.g., Alipour et al., 2017; Rouholamini and Mohammadian, 2015). CHPs are complex systems that generate electricity by burning fuel and, by recovering the waste heat, supply heat for space or water heating. If properly expanded with cooling units, such as absorption chillers and electric chillers (Gu et al., 2014), CHPs can satisfy also cooling demand (CCHPs). In particular, the main generation units of these systems are the prime movers, such as ICEs (Alahäivälä et al., 2015; Brandoni et al., 2014), FCs (Aki et al., 2016; Mao et al., 2010; Alipour et al., 2015; Shaneb et al., 2012; Anvari-Moghaddam et al., 2015; Elkazaz et al., 2016; Larsen et al., 2014), and MTs (Mao et al., 2010; Sheikhi et al., 2015), and the auxiliary boiler or furnace. They both burn fuel to generate electricity and heat, respectively. Biomass units are included among the dispatchable generating DERs as well (Dagdougui et al., 2012).

The most common non-dispatchable DERs are PV units and WTs. As their output is intermittent and it is difficult to predict, several techniques are commonly employed to model the stochastic behavior of non-dispatchable DERs, as we discuss in Section 4.6.

4.4.2. Transformation

Transformation resources refer to all DERs whose inputs and outputs are both secondary energy resources. Electric water heater uses electricity to heat water; electric heat pump (EHP) and AC system consume electricity to move heat from a cold source to a warm one. Absorption and compression chillers are coupled with prime mover in CCHP and they use waste heat or electricity to move heat between different fluids and satisfy cooling load (Gu et al., 2014). The most common transformation units are included in Fig. 3 within trapezoids.

In Alipour et al. (2017) and Rouholamini and Mohammadian (2015), a hydrogen production plant, composed by electrolyzer and H₂ storage tank, is included into the model to supply H₂ to a FC. The electrolyzer is included among the transformation resources as it converts electricity in another energy vector, i.e., hydrogen.

4.4.3. Storage

With the increasing amount of generated non-dispatchable energy, storage systems are gaining importance for optimal scheduling, as they can shift energy availability over time at the expenses of small losses. Among several types of storage, electrochemical energy storage (EES) and thermal energy storage (TES) devices are the most interesting for EMS at distribution level. We include in the former group also PEVs, if the battery can supply electricity back to the main grid when needed (Eid et al., 2016). On the other hand, if the power flow between a PEV and the main grid is unidirectional, that means, the vehicle's battery can only be charged, then it is considered as an electric load. Thermal storage devices are usually coupled with CHP units and allow excess thermal energy to be stored and used later in time by elevating

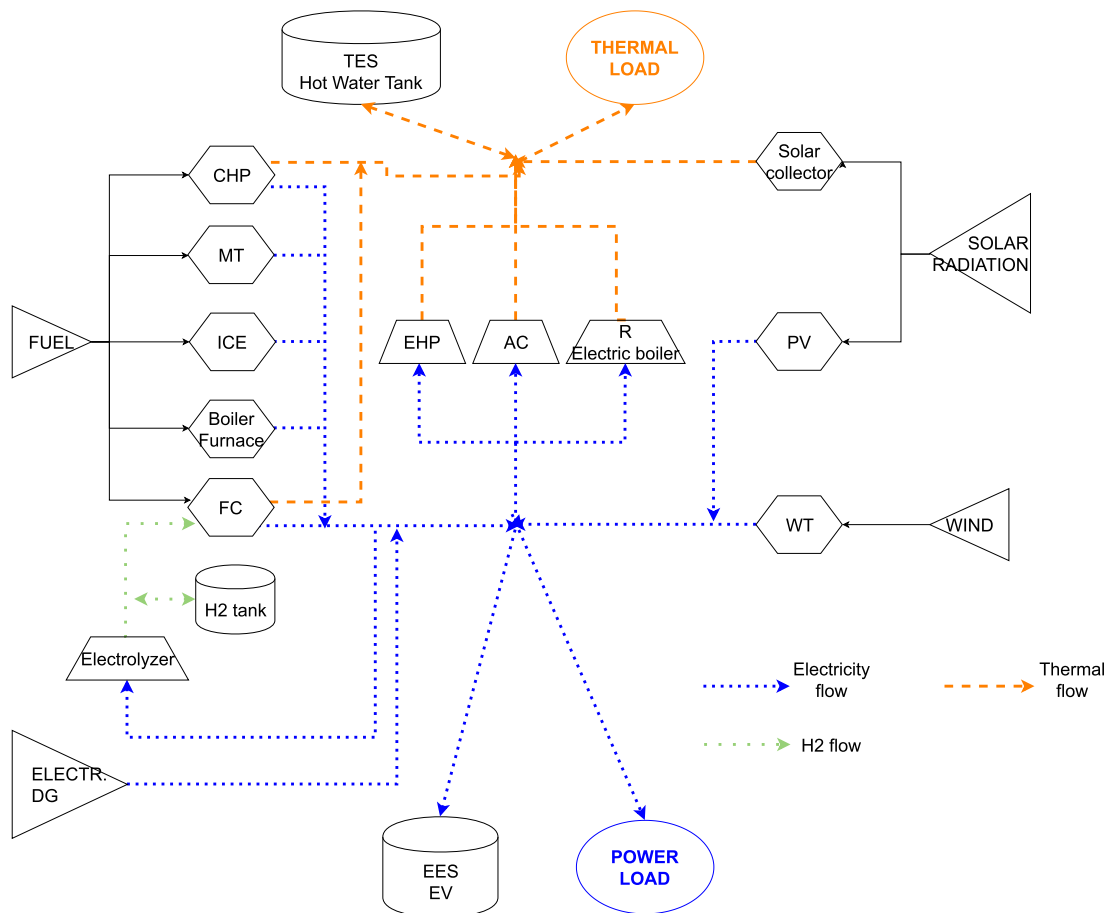


Fig. 3. DER: schematic representation of how generation, transformation, and storage DER are interconnected.

or lowering the temperature of a substance, such as water, or changing its phase, as with molten salt technology (Cabeza, 2012). Where a hydrogen plant is considered, a H₂ storage tank is also included (Alipour et al., 2017; Rouholamini and Mohammadian, 2015). In Fig. 3, electric, thermal, and hydrogen storage devices are represented by cylinders.

4.5. Load model

4.5.1. Aggregated vs per appliance

The power demand can be considered either as an aggregated load profile or as a combination of appliances, see Table 6. In the former case, how the single appliances contribute to shape the load profile is not further investigated. The profile can be composed of different shares, namely uncontrollable, programmable, and curtailable loads, depending on the control strategy that can be implemented (e.g., Brenna et al., 2015; Farmani et al., 2018; Mohsenzadeh and Pang, 2018; Salpakari and Lund, 2016). Another group of studies considers the contribution of different appliances to the final power demand, given their parameters, such as rated power, time window for its operation, duration of operation, and total energy consumption, often in combination with an aggregated uncontrollable load profile. When this approach is taken, it can be assumed the user sets some of these parameters, according to his own preferences.

4.5.2. Hybrid appliances

The most common appliances use only a single energy carrier during their operation, namely electricity, hot water, or gas. On the other hand, some devices can be supplied by multiple

energy carriers, which are used alternatively or in parallel to operate (Mauser et al., 2017). This type of appliances is referred to as *hybrid*, and its application within the context of MES is gaining interest in literature (Mauser et al., 2015, 2016, 2017; Fiorini and Aiello, 2018). In Mauser et al. (2016) and Mauser et al. (2015), the smart households are equipped with five hybrid appliances, namely washing machine, tumble dryer, dishwasher, oven, and hob; a hybrid kettle is also considered in Fiorini and Aiello (2018).

4.5.3. Thermal load

Thermal load can include hot water demand, space heating and cooling. As one can see in Table 6, the majority of the studies clearly define the thermal demand as hot water demand and/or space heating. However, a second group of works do not specify the purpose of the required heat. Moreover, the heating system may be assumed to follow a user-defined set-point, which can deviate within a certain range, in order to guarantee user's comfort. Beside electricity and thermal load, the energy hub proposed in Majidi et al. (2017b) considers the supply also of gas and water demands.

4.6. Uncertainties and information

Whatever system we model in terms of size, devices, and objectives, uncertainties may affect several parameters involved. In particular, RES productions, energy prices, weather conditions, and energy demands are subject to significant variation in time and can be difficult to predict. We identify three main types of approaches according to the level of accuracy about the future states of the system, namely perfect, forecasted, and non-forecasted imperfect information.

Table 5
Distributed energy resources.

Type of DER	Technology	Works	# of works
Dispatchable generation	C(C)HP	Holjevac et al. (2015), Aki et al. (2016), Alahäivälä et al. (2015), Alipour et al. (2015), Mao et al. (2010), Brandoni et al. (2014), Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Miyazato et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Tabar et al. (2017), Alipour et al. (2017), Shaneb et al. (2012), Ashouri et al. (2016), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Zhao et al. (2013), Kolen et al. (2017), Anvari-Moghaddam et al. (2017), Good and Mancarella (2017), Elkazaz et al. (2016), Huo et al. (2018), Javadi et al. (2017), Jiang et al. (2017), Kneiske et al. (2018), Larsen et al. (2014), Ma et al. (2017), Mauser et al. (2015), Braun et al. (2016), Neyestani et al. (2015), Rayati et al. (2015), Setlhaolo et al. (2017), Sheikhi et al. (2015), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Mohammadi et al. (2017), Parisio et al. (2015), Parisio et al. (2017), Rodriguez-diaz et al. (2017), Zhang et al. (2015) and Brenna et al. (2015)	49
	ICE	Alahäivälä et al. (2015) and Brandoni et al. (2014)	2
	Stirling Engine	Prinsloo et al. (2016)	1
	Boiler or Furnace	Aki et al. (2016), Alahäivälä et al. (2015), Brandoni et al. (2014), Majidi et al. (2017b), Alipour et al. (2017), Batić et al. (2016), Shaneb et al. (2012), Zhao et al. (2013), Kolen et al. (2017), Good and Mancarella (2017), Ha et al. (2017), Huo et al. (2018), Javadi et al. (2017), Jiang et al. (2017), Kneiske et al. (2018), Larsen et al. (2014), Ma et al. (2017), Mauser et al. (2016), Fiorini and Aiello (2018), Braun et al. (2016), Neyestani et al. (2015), Sheikhi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013), Sheikhi et al. (2015), Skarvelis-Kazakos et al. (2016), Nojavan et al. (2017), Majidi et al. (2017a), Holjevac et al. (2015), Alipour et al. (2015), Mao et al. (2010), Tabar et al. (2017), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Farmani et al. (2018), Mahoor et al. (2013), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Zhang et al. (2015) and Brenna et al. (2015)	40
	Biomass	Dagdougui et al. (2012)	1
Non-dispatchable generation	PV	Brandoni et al. (2014), Brahman et al. (2015), Miyazato et al. (2016), Majidi et al. (2017b), Batić et al. (2016), Ashouri et al. (2016), Kolen et al. (2017), Elkazaz et al. (2016), Ha et al. (2017), Huo et al. (2018), Kneiske et al. (2018), Ma et al. (2017), Lorestani et al. (2016), Mauser et al. (2016), Mauser et al. (2015), Braun et al. (2016), Mohsenzadeh and Pang (2018), Qayyum et al. (2015), Rayati et al. (2015), Razmara et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Shirazi and Jadid (2017), Zhang et al. (2013), De Angelis et al. (2013), Setlhaolo et al. (2017), Skarvelis-Kazakos et al. (2016), Nojavan et al. (2017), Majidi et al. (2017a), Dagdougui et al. (2012), Rouholamini and Mohammadian (2015), Holjevac et al. (2015), Mao et al. (2010), Safamehr and Rahimi-Kian (2015), Tabar et al. (2017), Kriett and Salani (2012), Anvari-Moghaddam et al. (2017), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Parisio et al. (2015), Parisio et al. (2017), Rodriguez-diaz et al. (2017), Brenna et al. (2015) and Zhang et al. (2015)	49
	High Concentrator PV	Brandoni et al. (2014)	1
	Solar thermal collector	Miyazato et al. (2016), Prinsloo et al. (2016), Dagdougui et al. (2012), Kriett and Salani (2012), Comodi et al. (2015), Ha et al. (2017) and Qi et al. (2017)	7
	Wind	Alipour et al. (2015), Mao et al. (2010), Majidi et al. (2017b), Tabar et al. (2017), Dagdougui et al. (2012), Rouholamini and Mohammadian (2015), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Brenna et al. (2015), Ma et al. (2017), Mahoor et al. (2013), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Rodriguez-diaz et al. (2017), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013) and Zhang et al. (2015)	18
Transformation	EHP and/or AC	Miyazato et al. (2016), Batić et al. (2016), Ashouri et al. (2016), Kolen et al. (2017), Good and Mancarella (2017), Ha et al. (2017), Javadi et al. (2017), Jiang et al. (2017), Lorestani et al. (2016), Mohsenzadeh and Pang (2018), Perez et al. (2016), Qayyum et al. (2015), Razmara et al. (2017), Huo et al. (2018), Salpakari and Lund (2016), Salpakari et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Shi et al. (2016), Shirazi and Jadid (2017), De Angelis et al. (2013), Qi et al. (2017), Rayati et al. (2015), Setlhaolo et al. (2017), Holjevac et al. (2015), Comodi et al. (2015), Parisio et al. (2015) and Parisio et al. (2017)	29
	Chillers	Brandoni et al. (2014), Brahman et al. (2015), Zhao et al. (2013), Brenna et al. (2015), Farmani et al. (2018), Ha et al. (2017), Javadi et al. (2017), Ma et al. (2017) and Sheikhi et al. (2016)	9
	Resistor or electric heater	Alahäivälä et al. (2015), Batić et al. (2016), Rouholamini and Mohammadian (2015), Good and Mancarella (2017), Mauser et al. (2016), Mauser et al. (2015), Fiorini and Aiello (2018), Salpakari and Lund (2016) and Setlhaolo et al. (2017)	9
	Electrolyzer	Alipour et al. (2017) and Rouholamini and Mohammadian (2015)	2

(continued on next page)

Having *perfect information* means that the future is known and uniquely determined. Although it is not a realistic condition, it may be useful to model and simulate complex systems.

This approach can be taken to model energy prices (e.g., Batić et al., 2016; Miyazato et al., 2016; Huo et al., 2018; Jiang et al., 2017; Ma et al., 2017; Lorestani et al., 2016; Moghaddas Tafreshi

Table 5 (continued).

Type of DER	Technology	Works	# of works
Storage	EES	Miyazato et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Alipour et al. (2017), Batić et al. (2016), Ashouri et al. (2016), Dagdougui et al. (2012), Setlhaolo et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Zhang et al. (2013), Good and Mancarella (2017), Ha et al. (2017), Javadi et al. (2017), Huo et al. (2018), Kneiske et al. (2018), Ma et al. (2017), Lorestani et al. (2016), Mauser et al. (2016), Razmara et al. (2017), Salpakari and Lund (2016), Alipour et al. (2015), Mao et al. (2010), Safamehr and Rahimi-Kian (2015), Prinsloo et al. (2016), Tabar et al. (2017), Parisio et al. (2015), Parisio et al. (2017), Rodriguez-diaz et al. (2017), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Mohsenzadeh and Pang (2018)-PEV, Qi et al. (2017)-PEV, Rayati et al. (2015)-PEV, Salpakari et al. (2017)-PEV, Moghaddas Tafreshi et al. (2016)-PEV, Mohammadi et al. (2017)-PEV, Sheikhi et al. (2016)-PEV, Shirazi and Jadid (2017)-PEV, Zhang et al. (2015)-PEV, De Angelis et al. (2013)-PEV, Brenna et al. (2015)-PEV and Brahman et al. (2015)-PEV	49
	TES	Aki et al. (2016), Alahäivälä et al. (2015), Brandoni et al. (2014), Brahman et al. (2015), Majidi et al. (2017b), Nojavan et al. (2017), Alipour et al. (2017), Shaneb et al. (2012), Kolen et al. (2017), Miyazato et al. (2016), Good and Mancarella (2017), Jiang et al. (2017), Kneiske et al. (2018), Larsen et al. (2014), Mauser et al. (2016), Mauser et al. (2015), Braun et al. (2016), Salpakari and Lund (2016), Salpakari et al. (2017), Shi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013), Ma et al. (2017), Neyestani et al. (2015), Qi et al. (2017), Majidi et al. (2017a), Holjevac et al. (2015), Alipour et al. (2015), Prinsloo et al. (2016), Tabar et al. (2017), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Farmani et al. (2018), Moghaddas Tafreshi et al. (2016), Zhang et al. (2015) and Brenna et al. (2015)	39
	H ₂ tank	Alipour et al. (2017) and Rouholamini and Mohammadian (2015)	2

et al., 2016; Razmara et al., 2017; Salpakari and Lund, 2016; Salpakari et al., 2017; Severini et al., 2013; Shirazi and Jadid, 2015, 2017; De Angelis et al., 2013), hourly electricity emission factors (Fiorini and Aiello, 2018; Braun et al., 2016), weather conditions (e.g., Batić et al., 2016; Nojavan et al., 2017; Jiang et al., 2017; Razmara et al., 2017; Shirazi and Jadid, 2017; Zhang et al., 2013; De Angelis et al., 2013), RES output (e.g., Brahman et al., 2015; Miyazato et al., 2016; Rouholamini and Mohammadian, 2015; Ha et al., 2017; Huber et al., 2013; Kneiske et al., 2018; Ma et al., 2017; Mahoor et al., 2013; Braun et al., 2016; Qayyum et al., 2015; Qi et al., 2017; Salpakari and Lund, 2016; Salpakari et al., 2017; Setlhaolo et al., 2017; Shirazi and Jadid, 2015; Skarvelis-Kazakos et al., 2016; De Angelis et al., 2013), and energy demands (e.g., Alahäivälä et al., 2015; Rouholamini and Mohammadian, 2015; Ha et al., 2017; Huber et al., 2013; Huo et al., 2018; Javadi et al., 2017; Kneiske et al., 2018; Ma et al., 2017; Lorestani et al., 2016; Mahoor et al., 2013; Neyestani et al., 2015; Salpakari and Lund, 2016; Salpakari et al., 2017; Severini et al., 2013; Skarvelis-Kazakos et al., 2016; Zhang et al., 2013). In some studies proposing DRPs, the total loads over a certain time horizon are known, but their scheduling is part of the optimization problem. This is the case for the power demand in Brahman et al. (2015), Mao et al. (2010), Miyazato et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Batić et al. (2016), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Safamehr and Rahimi-Kian (2015), Jiang et al. (2017), Ma et al. (2017), Fiorini and Aiello (2018), Braun et al. (2016), Perez et al. (2016), Qayyum et al. (2015), Setlhaolo et al. (2017), Severini et al. (2013), Sheikhi et al. (2015), Shirazi and Jadid (2015), Shi et al. (2016), Zhang et al. (2013), De Angelis et al. (2013), and for the thermal demand in Brahman et al. (2015), Mao et al. (2010), Batić et al. (2016), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017) and Sheikhi et al. (2015).

Starting from historical data, some studies use *forecasted information* by applying different forecasting techniques. A persistence forecast is used in Kneiske et al. (2018), assuming that the loads and PV production of two consecutive days are the same at the corresponding time, given historical PV time series and load demand data. In Alipour et al. (2015), wind speed

behavior, partially-shiftable electric load, and daily electricity prices are forecasted with autoregressive integrated moving average (ARIMA) model, based on time series analysis. The point estimate method $2m+1$ (Morales and Pérez-Ruiz, 2007) is used in Alipour et al. (2017) to forecast day-ahead prices and energy load, whereas Support Vector Machines (SVM) are used in Farmani et al. (2018) to predict new data, based on analyzed and preprocessed data collected by smart meters. A Radial Basis Function Networks (RBFN)-based prediction algorithm is proposed in Comodi et al. (2015) and Severini et al. (2013). In the former study, the data of the past 10 h are used to predict external temperature, solar irradiation, and PV output; in the latter, historical data are used to generate different profiles of solar irradiance and, hence, of solar production. A bottom-up approach based on historical data is used in Aki et al. (2016) to predict the energy demand, whereas solar irradiance, air temperature, and household consumptions are forecasted by time series method in Mohsenzadeh and Pang (2018). Air conditioning consumptions are estimated in Perez et al. (2016) by deriving a linear autoregressive model with exogenous input (ARX).

These forecasted information can be considered *perfect*, *non-deterministic*, or *probabilistic*. In the first case, no uncertainty on the magnitude of data (e.g., the wind speed) or the occurrence of an event (e.g., it is going to rain at a certain hour of the day) are modeled (e.g., Aki et al., 2016; Brandoni et al., 2014; Prinsloo et al., 2016). Forecasts are non-deterministic if they become available to the controller only at a short-notice, that means, the algorithm has to be updated accordingly (e.g., Comodi et al., 2015; Dagdougui et al., 2012; Ashouri et al., 2016; Kriett and Salani, 2012; Kneiske et al., 2018; Perez et al., 2016). Finally, forecasts are probabilistic when a probability distribution function (PDF) is associated to them (e.g., Alipour et al., 2015; Brenna et al., 2015; Farmani et al., 2018; Mohsenzadeh and Pang, 2018; Mauser et al., 2016, 2015). Markovian models are used to forecast the outages of DERs in Mao et al. (2010), as well as user behavior and PEV battery in Sheikhi et al. (2016).

A *non-forecasted imperfect information* approach consists in disregarding any forecasting method, while considering that data are not deterministically known in advance. Several studies use historical data or data available in the literature and add randomness (e.g., Holjevac et al., 2015; Safamehr and Rahimi-Kian, 2015;

Table 6
Load model.

Power			
Profile	<i>Aggregated</i>	Holjevac et al. (2015), Aki et al. (2016), Alahäivälä et al. (2015), Alipour et al. (2015), Brandoni et al. (2014), Mao et al. (2010), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Alipour et al. (2017), Batić et al. (2016), Shaneb et al. (2012), Dagdougui et al. (2012), Rouholamini and Mohammadian (2015), Kolen et al. (2017), Elkazaz et al. (2016), Good and Mancarella (2017), Ha et al. (2017), Huo et al. (2018), Javadi et al. (2017), Kneiske et al. (2018), Larsen et al. (2014), Ma et al. (2017), Lorestani et al. (2016), Neyestani et al. (2015), Qi et al. (2017), Razmara et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Sheikhi et al. (2015), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Prinsloo et al. (2016), Tabar et al. (2017), Kriett and Salani (2012), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mahoor et al. (2013), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017) and Rodriguez-diaz et al. (2017)	25
	<i>Per appliance</i>	Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Miyazato et al. (2016), Ashouri et al. (2016), Zhao et al. (2013), Jiang et al. (2017), Mauser et al. (2016), Fiorini and Aiello (2018), Braun et al. (2016), Mohsenzadeh and Pang (2018), Perez et al. (2016), Qayyum et al. (2015), Qi et al. (2017), Rayati et al. (2015), Setlhaolo et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013), De Angelis et al. (2013), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Parisio et al. (2015), Parisio et al. (2017), Zhang et al. (2015) and Brenna et al. (2015)	29
Demand response	<i>Shiftable (over time)</i>	Miyazato et al. (2016), Majidi et al. (2017b), Alipour et al. (2017), Batić et al. (2016), Ashouri et al. (2016), Jiang et al. (2017), Mauser et al. (2016), Fiorini and Aiello (2018), Braun et al. (2016), Mohsenzadeh and Pang (2018), Perez et al. (2016), Qayyum et al. (2015), Salpakari and Lund (2016), Severini et al. (2013), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shi et al. (2016), Zhang et al. (2013), De Angelis et al. (2013), Ma et al. (2017), Qi et al. (2017), Rayati et al. (2015), Setlhaolo et al. (2017), Sheikhi et al. (2015), Nojavan et al. (2017), Majidi et al. (2017a), Holjevac et al. (2015), Alipour et al. (2015), Safamehr and Rahimi-Kian (2015), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015) and Anvari-Moghaddam et al. (2017)	32
	<i>Shiftable (energy carriers)</i>	Fiorini and Aiello (2018) and Shirazi and Jadid (2017)	2
	<i>Curtailable</i>	Mao et al. (2010), Dagdougui et al. (2012), Zhao et al. (2013), Mohammadi et al. (2017) and Rodriguez-diaz et al. (2017)	5
	<i>Shiftable+Curtable</i>	Brahman et al. (2015), Brenna et al. (2015), Farmani et al. (2018), Good and Mancarella (2017), Mahoor et al. (2013) and Zhang et al. (2015)	6
	<i>User preferences</i>	Brahman et al. (2015), Ashouri et al. (2016), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Jiang et al. (2017), Mauser et al. (2016), Fiorini and Aiello (2018), Braun et al. (2016), Mohsenzadeh and Pang (2018), Parisio et al. (2015), Perez et al. (2016), Setlhaolo et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Shirazi and Jadid (2017), Zhang et al. (2013), Parisio et al. (2017) and Zhang et al. (2015)	20
Thermal			
Purpose	<i>General</i>	Holjevac et al. (2015), Alipour et al. (2015), Mao et al. (2010), Brandoni et al. (2014), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017), Brenna et al. (2015), Elkazaz et al. (2016), Huber et al. (2013), Kneiske et al. (2018), Lorestani et al. (2016), Mahoor et al. (2013), Braun et al. (2016), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Sheikhi et al. (2015), Shi et al. (2016), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013) and Zhang et al. (2015)	22
	<i>Space heating</i>	Alahäivälä et al. (2015), Miyazato et al. (2016), Alipour et al. (2017), Batić et al. (2016), Shaneb et al. (2012), Ashouri et al. (2016), Zhao et al. (2013), Kolen et al. (2017), Good and Mancarella (2017), Ha et al. (2017), Javadi et al. (2017), Jiang et al. (2017), Larsen et al. (2014), Mauser et al. (2016), Fiorini and Aiello (2018), Mohsenzadeh and Pang (2018), Neyestani et al. (2015), Razmara et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Sheikhi et al. (2016), Shirazi and Jadid (2017), De Angelis et al. (2013), Rayati et al. (2015), Setlhaolo et al. (2017), Dagdougui et al. (2012), Rouholamini and Mohammadian (2015), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Parisio et al. (2015) and Parisio et al. (2017)	36
	<i>Space cooling</i>	Brandoni et al. (2014), Safamehr and Rahimi-Kian (2015), Ashouri et al. (2016), Zhao et al. (2013), Anvari-Moghaddam et al. (2017), Ha et al. (2017), Javadi et al. (2017), Ma et al. (2017), Perez et al. (2016), Qayyum et al. (2015), Rayati et al. (2015), Razmara et al. (2017), Severini et al. (2013), Sheikhi et al. (2016) and De Angelis et al. (2013)	15
	<i>Cooking</i>	Brahman et al. (2015)	1
	<i>Hot water</i>	Aki et al. (2016), Alahäivälä et al. (2015), Brahman et al. (2015), Miyazato et al. (2016), Dagdougui et al. (2012), Kriett and Salani (2012), Rouholamini and Mohammadian (2015), Zhao et al. (2013), Good and Mancarella (2017), Larsen et al. (2014), Ma et al. (2017), Mauser et al. (2016), Fiorini and Aiello (2018), Neyestani et al. (2015), Qi et al. (2017), Rayati et al. (2015), Salpakari and Lund (2016), Setlhaolo et al. (2017), Shirazi and Jadid (2015), Shirazi and Jadid (2017), Anvari-Moghaddam et al. (2015), Comodi et al. (2015), Farmani et al. (2018) and Rodriguez-diaz et al. (2017)	24

(continued on next page)

Tabar et al., 2017; Elkazaz et al., 2016; Larsen et al., 2014; Mohammadi et al., 2017; Mohsenzadeh and Pang, 2018; Neyestani et al., 2015; Good and Mancarella, 2017; Razmara et al., 2017; Rodriguez-diaz et al., 2017; Zhang et al., 2015). For instance,

an error range for each available data series, such as energy demands, wind speed, and PV production (Holjevac et al., 2015; Elkazaz et al., 2016; Shaneb et al., 2012; Rodriguez-diaz et al., 2017). The work presented in Safamehr and Rahimi-Kian (2015),

Table 6 (continued).

Thermal			
Demand response	Shiftable	Batić et al. (2016), Ashouri et al. (2016), Kriett and Salani (2012), Kolen et al. (2017), Sheikhi et al. (2015) and Shi et al. (2016)	6
	Curtable	Mao et al. (2010), Brahman et al. (2015), Dagdougui et al. (2012), Anvari-Moghaddam et al. (2015), Zhao et al. (2013), Anvari-Moghaddam et al. (2017), Good and Mancarella (2017), Braun et al. (2016), Mohsenzadeh and Pang (2018), Parisio et al. (2015), Perez et al. (2016), Razmara et al. (2017), Salpakari et al. (2017), Setlhaolo et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Shirazi and Jadid (2017), De Angelis et al. (2013), Parisio et al. (2017) and Zhang et al. (2015)	20
	Shiftable+Curtable	Alipour et al. (2017)	1
	User preferences	Ashouri et al. (2016), Anvari-Moghaddam et al. (2015), Braun et al. (2016), Mohsenzadeh and Pang (2018), Parisio et al. (2015), Parisio et al. (2017), Perez et al. (2016), Rayati et al. (2015), Razmara et al. (2017), Salpakari et al. (2017), Setlhaolo et al. (2017), Severini et al. (2013), Shirazi and Jadid (2015), Shirazi and Jadid (2017) and De Angelis et al. (2013)	15

Tabar et al. (2017), Jiang et al. (2017), Moghaddas Tafreshi et al. (2016), Mohsenzadeh and Pang (2018), Good and Mancarella (2017), Razmara et al. (2017) and Zhang et al. (2015) considers PDFs with different parameters depending on the variables. PDFs are used in Qi et al. (2017) to simulate the arrival and departure time of the electric vehicles. In Mohammadi et al. (2017), three scenarios are simulated by associating different probabilities to possible values of electricity and gas prices, load, and wind speed. Uncertainties in user behavior to select energy carriers and respond to DRPs are modeled in Neyestani et al. (2015) with a normal distribution, with time-dependent parameters.

Another way of modeling uncertainties is to use *real-time data* (Aki et al., 2016; Prinsloo et al., 2016), so that the results are not influenced by uncertainties, but only based on past and present states of the system. A combination of non-deterministic forecasted information and real-time data is applied in Kneiske et al. (2018). A high-level controller schedules the operation of storage devices, CHP, and boiler every ten minutes, according to forecasted data available every six hours. Between two time steps, a low-level controller corrects the setpoints of the components based on their real-time status. Historical demand data are used in Larsen et al. (2014) to simulate the real-time control of the DERs of a group of households; the EMS receives the information of power and heat demands every 5 min, hence it has to adjust the scheduling accordingly. Similarly, the local EMSs and the aggregator update the scheduling every 10 min based on new available information and heating requirements in Parisio et al. (2015) and Parisio et al. (2017). In De Angelis et al. (2013), the EMS schedules appliances and thermal loads based on perfect price, weather, and RES production information. Real-time changes, e.g., a new task or the arriving/leaving of a PEV, are handled by recomputing the scheduling for the remaining period.

4.7. Grid connections

Optimal scheduling depends on the actual interconnectivity and model of the distribution grids involved.

4.7.1. Grid model

Power lines as well as pipes have physical characteristics determining the maximum amount of energy they can carry and energy losses during transportation and distribution. In power systems the amount of power a line or a cable can carry is limited, due to constraints over voltage drop and thermal effects on conductors and system equipment. Moreover, transmitting electricity between two nodes of the grid causes power losses along the lines mainly due to conductors' resistance (Glover et al., 2011). Similarly, the type of pipes and the maximum allowed pressure drop determine the maximum gas flow, and friction causes energy losses (Acha and Hernandez-Aramburo, 2008). Grid infrastructure can significantly affect the operation, as electricity (and gas) flow

is determined by the line (pipe) parameters and voltage (pressure) difference between nodes (Acha and Hernandez-Aramburo, 2008). Given the complexity of these infrastructures, we can distinguish different approaches, as summarized in Table 7. The most common approach is to neglect the grid structure and consider one for which the MES and stand-alone DERs, if any, are connected in one single point, where all energy exchanges with the main grid occur. This model is referred to as “single-busbar model” (SBB) Connections between these entities and the main grid can be modeled as *constrained*, i.e., a maximum amount of power can be exchanged during a time interval, or *unconstrained*, if this limitation is neglected. When a constrained approach is taken, there is a limit on the maximum power that can be exchanged with the main grid. Further constraints can be imposed on the exchanged power variation between two consecutive time steps (Miyazato et al., 2016) or according to the transformer rated capacity (Majidi et al., 2017b). Constraints are defined for both active and reactive power in Good and Mancarella (2017) in order to fulfill the network capacities. The hourly amount of gas imported from the main network can also be limited within a certain range (Majidi et al., 2017b; Ha et al., 2017; Huo et al., 2018; Ma et al., 2017; Neyestani et al., 2015), as well as the imported water (Majidi et al., 2017b).

Multi-energy systems may be connected not only to the main grid, but also among each other to exchange locally produced energy (Aki et al., 2016; Huo et al., 2018). These connections can be either unconstrained (Aki et al., 2016; Huber et al., 2013; Kolen et al., 2017; Larsen et al., 2014; Salpakari et al., 2017) or constrained. The studies adopting this approach belong to the “Interconnected” groups and are listed in Table 7. Four residential units are connected in Aki et al. (2016) in order to exchange both electricity and heat, sharing FC-CHP systems, back-up boilers, and storage devices. Larger systems are simulated in Huber et al. (2013), Larsen et al. (2014) and Salpakari et al. (2017), where ten to thirty smart homes that can exchange power, improving the integration of CHP units and/or PV panels, whereas almost 150 homes are considered in Kolen et al. (2017).

The counter approach is to locate sources and loads within the grid and consider how the energy is dispatched along the lines following the available connections. In this case, the physical infrastructure of the grid is taken into account, although is it usually simplified. The transmission grid is modeled as a graph in Jiang et al. (2017), where the nodes represent power plants, both traditional and renewable, and aggregated loads. The power flows are constrained by the capacity of the lines and their physical connections, which are derived from two IEEE-buses. Active power losses are calculated in Mohsenzadeh and Pang (2018) by running a load flow on a radial grid; then, such losses are allocated to each node, based on its position within the grid. A constrained power flow analysis is run on a modified version of the IEEE-13-node distribution feeder in Razmara et al. (2017), in order to evaluate the feasibility of building load profile. The

Table 7

Grid connection.

Electricity supply			
Model	<i>SBB Constrained</i>	Miyazato et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017), Batić et al. (2016), Ashouri et al. (2016), Good and Mancarella (2017), Ha et al. (2017), Huo et al. (2018), Ma et al. (2017), Fiorini and Aiello (2018), Neyestani et al. (2015), Qayyum et al. (2015), Qi et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Setlhaolo et al. (2017), Severini et al. (2013), Skarvelis-Kazakos et al. (2016), De Angelis et al. (2013), Anvari-Moghaddam et al. (2015), Farmani et al. (2018), Mahoor et al. (2013), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Parisio et al. (2017) and Brenna et al. (2015)	28
Model	<i>SBB Unconstrained</i>	Holjevac et al. (2015), Alahäivälä et al. (2015), Alipour et al. (2015), Mao et al. (2010), Brandoni et al. (2014), Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Alipour et al. (2017), Shaneb et al. (2012), Dagdougui et al. (2012), Kriett and Salani (2012), Rouholamini and Mohammadian (2015), Zhao et al. (2013), Javadi et al. (2017), Kneiske et al. (2018), Lorestani et al. (2016), Perez et al. (2016), Rayati et al. (2015), Sheikhi et al. (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Zhang et al. (2013), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Huber et al. (2013), Parisio et al. (2015), Rodriguez-diaz et al. (2017) and Zhang et al. (2015)	29
	<i>Interconnected Unconstr.</i>	Aki et al. (2016), Elkazaz et al. (2016), Huber et al. (2013), Kolen et al. (2017) and Salpakari et al. (2017)	5
	<i>Physical grid</i>	Jiang et al. (2017), Mohsenzadeh and Pang (2018) and Razmara et al. (2017)	3
Working mode	<i>On grid</i>	Holjevac et al. (2015), Aki et al. (2016), Alahäivälä et al. (2015), Alipour et al. (2015), Mao et al. (2010), Brandoni et al. (2014), Brahman et al. (2015), Safamehr and Rahimi-Kian (2015), Miyazato et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017), Alipour et al. (2017), Batić et al. (2016), Shaneb et al. (2012), Ashouri et al. (2016), Dagdougui et al. (2012), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Kolen et al. (2017), Zhao et al. (2013), Anvari-Moghaddam et al. (2017), Comodi et al. (2015), Brenna et al. (2015), Farmani et al. (2018), Elkazaz et al. (2016), Good and Mancarella (2017), Ha et al. (2017), Huber et al. (2013), Huo et al. (2018), Jiang et al. (2017), Kneiske et al. (2018), Ma et al. (2017), Lorestani et al. (2016), Mahoor et al. (2013), Mauser et al. (2016), Mauser et al. (2015), Fiorini and Aiello (2018), Moghaddas Tafreshi et al. (2016), Mohsenzadeh and Pang (2018), Neyestani et al. (2015), Parisio et al. (2017), Parisio et al. (2015), Qayyum et al. (2015), Qi et al. (2017), Rayati et al. (2015), Razmara et al. (2017), Rodriguez-diaz et al. (2017), Salpakari and Lund (2016), Salpakari et al. (2017), Setlhaolo et al. (2017), Severini et al. (2013), Sheikhi et al. (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013), Zhang et al. (2015) and De Angelis et al. (2013)	61
	<i>Off grid</i>	Holjevac et al. (2015), Alipour et al. (2015), Mao et al. (2010), Prinsloo et al. (2016), Brenna et al. (2015), Elkazaz et al. (2016) and Mohammadi et al. (2017)	7
Fuel supply			
Model	<i>SBB Constrained</i>	Majidi et al. (2017b), Ha et al. (2017), Huo et al. (2018), Ma et al. (2017) and Neyestani et al. (2015)	5
	<i>SBB Unconstrained</i>	Alahäivälä et al. (2015), Nojavan et al. (2017), Majidi et al. (2017a), Alipour et al. (2017), Batić et al. (2016), Shaneb et al. (2012), Kriett and Salani (2012), Anvari-Moghaddam et al. (2015), Zhao et al. (2013), Kolen et al. (2017), Anvari-Moghaddam et al. (2017), Brenna et al. (2015), Elkazaz et al. (2016), Good and Mancarella (2017), Huber et al. (2013), Jiang et al. (2017), Javadi et al. (2017), Kneiske et al. (2018), Mahoor et al. (2013), Mauser et al. (2016), Fiorini and Aiello (2018), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Parisio et al. (2015), Parisio et al. (2017), Rayati et al. (2015), Rodriguez-diaz et al. (2017), Setlhaolo et al. (2017), Severini et al. (2013), Sheikhi et al. (2015), Sheikhi et al. (2016), Shi et al. (2016), Shirazi and Jadid (2017), Skarvelis-Kazakos et al. (2016), Zhang et al. (2013), Zhang et al. (2015) and Zhang et al. (2015)	34

Only studies that explicitly refer to a fuel supply grid are included in the Table.

technical limits of lines, transformers, and capacitors are taken into account.

As for the fuel grid, the MESs do not usually produce fuel, hence the only possible connection is with the main distribution grid and it can be constrained or unconstrained. In Table 7, only studies that explicitly refer to a fuel supply grid are included.

Some studies include the possibility to exchange thermal power in a heat network, such as Aki et al. (2016), Huo et al. (2018), Elkazaz et al. (2016) and Majidi et al. (2017b)

4.7.2. Grid-connected vs. Islanded modes

The majority of studies consider the possibility to work in grid-connected mode, that means, energy is exchanged between the considered system and the main grid, as illustrated in Table 7. Some researches investigate the system behavior also in the case of off-grid mode, when it has to be flexible enough to balance production and consumption, without the possibility of buying from and selling to the grid energy.

4.8. Environmental considerations

The majority of reviewed studies focuses on economic goals, and only a smaller group of 15 studies includes environmental goals among objective functions (see Table 8). In these cases, the optimization problem includes either the minimization of the equivalent costs of pollutants (Mao et al., 2010; Brandoni et al., 2014; Rayati et al., 2015; Setlhaolo et al., 2017; Shaneb et al., 2012) or of their amount in tons (Brahman et al., 2015; Prinsloo et al., 2016; Majidi et al., 2017b; Nojavan et al., 2017; Majidi et al., 2017a; Tabar et al., 2017; Fiorini and Aiello, 2018; Braun et al., 2016; Mohammadi et al., 2017; Skarvelis-Kazakos et al., 2016). Another environmental goal can be the minimization of primary energy consumption cost (Brandoni et al., 2014). Emissions are due to local generation by DERs, imported electricity, and/or imported gas for cooking purposes.

Few papers draw *ex-post* environmental conclusions, usually quantifying the CO₂ emissions due to local production of electricity by burning fuel and importing electricity from the main grid (see Table 8).

Table 8
Environmental considerations.

Source of emission	Within the objective function	Ex-post
DER	Prinsloo et al. (2016) and Mao et al. (2010)	Holjevac et al. (2015) and Moghaddas Tafreshi et al. (2016)
Import of electricity	Setlhaolo et al. (2017)	
DER + import of electricity	Brandoni et al. (2014), Brahman et al. (2015), Nojavan et al. (2017), Majidi et al. (2017a), Tabar et al. (2017), Shaneb et al. (2012), Braun et al. (2016), Rayati et al. (2015), Skarvelis-Kazakos et al. (2016) and Mohammadi et al. (2017)	Aki et al. (2016) and Ma et al. (2017)
DER + import of electricity and gas	Majidi et al. (2017b) and Fiorini and Aiello (2018)	

The grid emission factor used for the estimation of pollutants due to imported electricity has been defined as a constant value in the majority of the studies, according to the generation mix of the main grid (Brandoni et al., 2014; Brahman et al., 2015; Majidi et al., 2017b; Nojavan et al., 2017; Majidi et al., 2017a; Tabar et al., 2017; Shaneb et al., 2012; Ma et al., 2017; Mohammadi et al., 2017; Rayati et al., 2015; Setlhaolo et al., 2017; Skarvelis-Kazakos et al., 2016). In Aki et al. (2016), it presents a time-of-use variation, being one third higher during peak-time (7–23 h), while in Fiorini and Aiello (2018) and Braun et al. (2016), a dynamic CO₂ intensity factor is defined based on the hourly energy mix.

5. Optimization techniques

Next, we overview the main optimization techniques applied to the scheduling problem. In particular, we discuss the MO problem formulation, how to take into account forecast uncertainties, and several optimization algorithms. Methods and techniques are summarized in Table 9.

5.1. Multi-objective problem formulation

A general formulation of a MO optimization problem is posed as follows (Marler and Arora, 2004):

$$\begin{aligned} & \min_{\mathbf{x}} \mathbf{F}(\mathbf{x}) \\ \text{subject to } & g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, \dots, m \\ & \text{s.t. } h_l(\mathbf{x}) = 0, \quad l = 1, 2, \dots, e \end{aligned}$$

where $\mathbf{F}(\mathbf{x})$ is the objective function over decision variables \mathbf{x} , m is the number of inequality constraints, and e is the number of equality constraints.

The objective functions can have varying degrees of importance, reflecting the preferences of the decision-maker. Let now consider some of the most common approaches proposed.

The *weighted sum* method defines a weight for each objective function, given that the sum of all weights is one. In this way, objectives with higher weights will have a greater impact on determining the final solution. By adding these factors, the MO problem is reduced to a SO one, that is the weighted sum of all objective functions. The *bounded objective* methods minimize one objective while all others are translated into additional constraints by limiting their values within a given range. If only the upper bound of this range is considered, then it is called ϵ -*constraint method*. By varying the upper bound of each objectives, a set of Pareto optimal solutions is provided (Marler and Arora, 2004). For example, the ϵ -constraint method is used in Brahman et al. (2015), Nojavan et al. (2017) and Tabar et al. (2017) to minimize both energy cost and emissions. A similar approach is also taken in Kolen et al. (2017) to compare the multi-agent decentralized approach with a centralized benchmark. Local objectives are solved and added as constraints within the global objective, so that the minimization of switching events of each local agent are included in the goal of flattening the energy demand of the cluster agent.

The *Pareto front* is a trade-off curve on which all optimal solutions of a MO problems lie. It helps a decision-maker selecting the best trade-off, after seeing a portfolio of optimal solutions (Beaudin and Zareipour, 2015). This approach is used in Miyazato et al. (2016) to compare and select the best trade-off between electricity costs and regulation efforts, while in Braun et al. (2016) an approximation of the Pareto front is used to compare the performances of different algorithms given a MO problems with four objective functions. In Majidi et al. (2017b), Nojavan et al. (2017) and Majidi et al. (2017a), a Pareto front is obtained by tuning the weighting factors and the best trade-off solution is found by means of max–min fuzzy technique.

Function transformation methods refer to a group of approaches that modify the original objective functions, for example by scalarizing them given the maximum objective function value (Marler and Arora, 2004). An approach based on membership degree of fuzzy set theory is adopted in Mao et al. (2010), and the MO original problem is translated into a non-linear SO one.

5.2. Dealing with uncertainties

Renewable production and end-user's demand forecasts are never fully accurate, and uncertainties can significantly affect the results. A *Stochastic Optimization* approach considers that the decision made at a given time is not affected by information about uncertain data available at a later time period in the planning horizon (Beaudin and Zareipour, 2015). At each time step, the future values of uncertain parameters are estimated considering different PDFs (e.g., Alipour et al., 2015, 2017; Safamehr and Rahimi-Kian, 2015; Tabar et al., 2017; Farmani et al., 2018; Mohsenzadeh and Pang, 2018; Neyestani et al., 2015). This time evolving system can be represented through a probabilistic scenario tree; the starting node of the problem is the “root” and, by following branches, different stages are reached until the final nodes, called “leaves”. Each path from the root to a leaf is a possible scenario (Rockafellar, 2001) and has a probability of occurrence. Alternatively, tens of possible scenarios are generated by combining previously selected different profiles for uncertain parameters, such as energy prices, weather conditions, power demands, and renewable generation (e.g., Good and Mancarella, 2017; Moghaddas Tafreshi et al., 2016; Mohammadi et al., 2017). Among all scenarios, those with the highest probability are selected via reduction techniques and used for running the optimization problem. The user behavior is modeled as a Markov chain in Rayati et al. (2015), showing periodic, daily and weekly patterns.

Model Predictive Control (MPC) is based on the idea of approximating a long-horizon optimal control problem by a short-horizon one. At each time step, the algorithm estimates the future behavior of the system based on current forecasts, and finds an optimal state based on the prediction. Next, new forecasts are available, and the procedure is repeated. In other words, the original optimization problem addresses the forecast uncertainties by sequentially making short-term decision, based on new

Table 9

Problem formulation.

Techniques for multi-objective problems			
Weighted sum		Prinsloo et al. (2016), Brandoni et al. (2014), Majidi et al. (2017b), Nojavan et al. (2017), Majidi et al. (2017a), Anvari-Moghaddam et al. (2015), Anvari-Moghaddam et al. (2017), Setlhaolo et al. (2017) and Shirazi and Jadid (2015)	9
Bounded objective		Tabar et al. (2017), Brahman et al. (2015), Nojavan et al. (2017) and Kolen et al. (2017)	4
Pareto front		Miyazato et al. (2016), Majidi et al. (2017b), Nojavan et al. (2017) and Majidi et al. (2017a)	4
Fuzzy set theory		Mao et al. (2010)	1
Dealing with uncertainties			
Stochastic Optimization		Alipour et al. (2015), Alipour et al. (2017), Safamehr and Rahimi-Kian (2015), Tabar et al. (2017), Farmani et al. (2018), Good and Mancarella (2017), Moghaddas Tafreshi et al. (2016), Mohammadi et al. (2017), Mohsenzadeh and Pang (2018), Neyestani et al. (2015) and Rayati et al. (2015)	11
Model Predictive Control		Holjevac et al. (2015), Ashouri et al. (2016), Dagdougui et al. (2012), Kriett and Salani (2012), Comodi et al. (2015), Prinsloo et al. (2016), Aki et al. (2016), Kneiske et al. (2018), Larsen et al. (2014), Parisio et al. (2015), Parisio et al. (2017), Perez et al. (2016), Razmara et al. (2017) and Zhang et al. (2015)	14
Approaches			
Mathematical method	LP	Shaneb et al. (2012), Batić et al. (2016), Brandoni et al. (2014), Mahoor et al. (2013), Salpakari et al. (2017) and Severini et al. (2013)	6
	MIP	Rodriguez-diaz et al. (2017)	1
	MILP	Aki et al. (2016), Brahman et al. (2015), Majidi et al. (2017b), Ashouri et al. (2016), Good and Mancarella (2017), Jiang et al. (2017), Kneiske et al. (2018), Ma et al. (2017), Fiorini and Aiello (2018), Mohsenzadeh and Pang (2018), Neyestani et al. (2015), Perez et al. (2016), Qayyum et al. (2015), Qi et al. (2017), Severini et al. (2013), Shirazi and Jadid (2017), Zhang et al. (2013), De Angelis et al. (2013), Nojavan et al. (2017), Majidi et al. (2017a), Holjevac et al. (2015), Prinsloo et al. (2016), Tabar et al. (2017), Kriett and Salani (2012), Comodi et al. (2015), Farmani et al. (2018), Huber et al. (2013), Mohammadi et al. (2017), Parisio et al. (2015), Parisio et al. (2017) and Zhang et al. (2015)	31
	NLP	Huo et al. (2018)	1
	MINLP	Alipour et al. (2015), Alipour et al. (2017), Anvari-Moghaddam et al. (2015), Farmani et al. (2018), Ha et al. (2017), Javadi et al. (2017), Setlhaolo et al. (2017) and Shirazi and Jadid (2015)	8
	(MI)QP	Dagdougui et al. (2012) and Larsen et al. (2014)	2
	DP	Alahäivälä et al. (2015), Mauser et al. (2016), Mauser et al. (2015) and Salpakari and Lund (2016)	4
	PSO	Mao et al. (2010), Elkazaz et al. (2016), Huo et al. (2018) and Moghaddas Tafreshi et al. (2016)	4
	ABC	Safamehr and Rahimi-Kian (2015)	1
	IWO	Loresani et al. (2016)	1
Meta-heuristic	GA	Miyazato et al. (2016), Elkazaz et al. (2016), Mauser et al. (2016), Mauser et al. (2015) and Severini et al. (2013)	5
	GSA	Rouholamini and Mohammadian (2015)	1
Heuristic	Reinforcement learning	Rayati et al. (2015) and Sheikhi et al. (2016)	2
	Rule-based heuristic	Salpakari and Lund (2016), Zhang et al. (2013) and Kolen et al. (2017)	3
	Game-theory based	Sheikhi et al. (2015)	1
	Greedy algorithm	Shi et al. (2016)	1

short-term forecasts. MPC is applied in several works to minimize the impact of uncertainties on the optimal scheduling problem. Such uncertainties can affect wind speed forecasts (Holjevac et al., 2015), solar (Ashouri et al., 2016; Zhang et al., 2015) and wind production (Zhang et al., 2015), load demand (Zhang et al., 2015), and electricity prices (Zhang et al., 2015). In Dagdougui et al. (2012), Kriett and Salani (2012) and Razmara et al. (2017), RES production, electricity prices, and/or weather conditions are derived from historical data and are available without uncertainties to the EMS at short notice, e.g. with a 7.5-h (Kriett and Salani, 2012) or 6-h (Razmara et al., 2017) prediction horizon (Kriett and Salani, 2012). Similarly, air conditioning consumptions are forecasted every 12 h in Perez et al. (2016), and the MPC system adjusts the thermostat accordingly. In Aki et al. (2016) and Prinsloo et al. (2016), the EMS optimally schedules the available DERs for the next day, according to an accurate forecast. Then, it receives real-time data of the energy consumptions and, consequently, it has to revise the planned operational scheduling. In Kneiske et al. (2018), forecasted PV generation and demand time series are available every 6 h. A MPC optimizes the components operation every 10 min, while a low-level controller adjusts their set-points according to real-time data with 1 min resolution. The authors of Kneiske et al. (2018) proposes also an alternative control mode, where the MPC does not repeat the optimization every 10 min, but only if the low-level controller detects a too

high offset between actual and predicted values or if the end of the 6-h prediction horizon is reached. A distributed MPC is applied to a network of households in Larsen et al. (2014), with the aim of scheduling the operation of CHP systems and heat storage devices in real-time. The resolution of the data and the proposed algorithm are, indeed, one minute, while the prediction horizon of the MPC is five minutes. In Parisio et al. (2015) and Parisio et al. (2017), the daily operation of DERs and flexible loads is the result of an iterative optimization process which is repeated every 10 min, when new informations on prices, weather conditions, and renewable generation are available.

5.3. Approaches: Mathematical methods

Linear Programming (LP) is the simplest mathematical optimization method, where objectives and constraints are expressed as linear functions (Batić et al., 2016; Shaneb et al., 2012; Salpakari et al., 2017), and variables assume real, continuous values. When all decision variables are integer, then the problem is called Integer Programming (IP) problem, while when some variables, but not all, are restricted to be integer, then it is a Mixed-Integer Programming (MIP) problem (Rodriguez-diaz et al., 2017). Investigating the algorithm to solve these kinds of problems is outside the scope of this work; the interested reader is

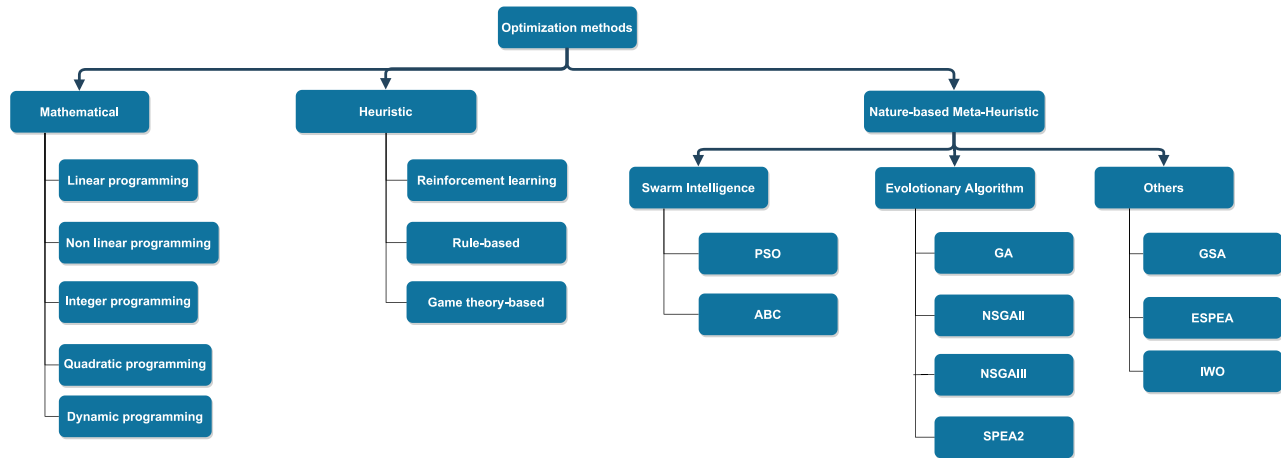


Fig. 4. Classification of optimization methods found in reviewed papers.

referred to Schrijver (1986) and Floudas and Lin (2005). *Mixed-Integer Linear Programming (MILP)* formulation is used for both SO (e.g., Holjevac et al., 2015; Aki et al., 2016; Ashouri et al., 2016; Kriett and Salani, 2012; Farmani et al., 2018; Kneiske et al., 2018; Ma et al., 2017; Fiorini and Aiello, 2018; Mohsenzadeh and Pang, 2018; Parisio et al., 2015, 2017; Zhang et al., 2015) and MO problems, which are reduced to a SO one by means of techniques presented in Section 5.1 (e.g., Brahman et al., 2015; Prinsloo et al., 2016; Majidi et al., 2017b; Nojavan et al., 2017; Tabar et al., 2017; Majidi et al., 2017a; Mohammadi et al., 2017; Severini et al., 2013; De Angelis et al., 2013). In Brandoni et al. (2014), LP technique is adopted and applied in an iterative procedure in order to overcome the non-linear behavior of ICE unit.

Non-Linear Programming (NLP) refers to optimization problems with non-linear objective function and/or constraints, such as the minimization costs problem formulated in Rouholamini and Mohammadian (2015). In case the problem includes also integer variables, then it is referred to as a *Mixed-Integer Non-Linear Programming (MINLP)* problem.

Quadratic Programming (QP) formulates the optimization objective as a quadratic function, as in Dagdougui et al. (2012). The optimization problem in Larsen et al. (2014) consists of a quadratic objective function and binary variables represent the on-off status of DERs; hence the model is formulated as a *Mixed-Integer Quadratic Programming (MIQP)* problem.

Dynamic Programming (DP) divides a complex problem into several simpler sub-problems that are solved recursively, by storing their solutions. DP is used to minimized energy costs of a residential micro-CHP system in Alahäivälä et al. (2015). In Salpakari and Lund (2016), it is used to approximate a NLP problem representing one-year energy costs, by considering sequential 24-h horizons. In Mauser et al. (2016, 2015), the operation scheduling of several devices is divided in corresponding sub-problems, called Interdependent Problem Parts.

5.4. Approaches: Heuristic techniques

Heuristic techniques are designed to find a sufficiently good solution by following prescribed rules. The main idea is to find a balance between the solution quality and the computation time (Blum and Roli, 2003; Bianchi et al., 2009). Although heuristics cannot guarantee an optimal solution, they usually help finding good-enough solutions, while significantly reducing the computational burden of alternative mathematical methods (Beaudin and Zareipour, 2015). Heuristics are typically domain-specific and their performance depends on the system they are implemented in. Moreover, they require a certain experience and knowledge of

the system itself (Beaudin and Zareipour, 2015). For instance, the NEST thermostat is smart device that uses heuristics to control the indoor temperature. By collecting usage statistics and environmental data of the local space, the device “learns” the user’s behavior and implements rules (e.g., turning on and off the gas boiler) in order to satisfy user’s temperature preferences (Parker et al., 2016).

The *reinforcement learning* method is applied in Rayati et al. (2015) and Sheikhi et al. (2016) with the aim of minimizing the total costs of a large residential energy hub and a single residential prosumer, respectively. The EMS learns which actions yield rewards (positively reinforced) or punishments (negatively reinforced), given a stochastic Markovian user behavior. The method achieves a near-optimal solution by means of the Q-learning algorithm (Watkins and Dayan, 1992).

In Salpakari and Lund (2016) and Zhang et al. (2013), a cost-optimal scheduling is compared to a *rule-based* heuristic one. In Salpakari and Lund (2016), the heuristic control aims at maximizing the PV self-generation, by following a list of priorities in case of PV power surplus. For instance, first, shiftable appliances are moved in the surplus period; then, the remaining surplus is stored in ESS, or converted to heat. As the last resort, the surplus may be curtailed. In Zhang et al. (2013), the heuristic scheduling turns on appliances at their earliest starting time, irrespective of energy prices. A *greedy algorithm* is proposed in Shi et al. (2016), which allocates resources according to a hierarchy. The residential devices are ranked according to their flexibility, from uncontrollable devices to shiftable appliances and storage. The algorithm allocates electricity and heat starting from the less flexible devices, and set the operation conditions for generation DERs. A near-optimal solution is found, significantly reducing the computational time, compared to a mathematical method.

In Sheikhi et al. (2015), the scheduling problem is formulated as a non-cooperative game and solved with a *game theoretic*-based algorithm. The algorithm is proven to converge to a Nash equilibrium, which determines the energy strategy profile that minimizes the user’s bills, while maximizing the energy utilities’ profit.

5.5. Approaches: Nature-based meta-heuristic methods

Meta-heuristic methods are high level procedures to find a sufficiently good solution by exploiting some features of the search-space. A significant advantage of meta-heuristic algorithms is to be problem-agnostic, that means, they do not require special knowledge of the problem to be solved and can be applied to a wide range of different optimization problems (Blum

and Roli, 2003). Meta-heuristics may combine multiple low-level heuristics and make use of their domain-specific knowledge in order to find a better near-optimal solutions (Gamarra and Guerrero, 2015). Among others, nature-based meta-heuristics are an active area of research (Nanda and Panda, 2014). A first group of nature-based meta-heuristics is inspired by the behavior of a group of animals interacting with each other and with the environment, and it is referred to as *Swarm intelligence* (Nanda and Panda, 2014). In *Particle Swarm Optimization* (PSO), solutions are called particles and are areas in a search space of the given problem. Each particle moves toward the best solutions according to its current and previous best positions, as well as the knowledge of the other particles in the swarm (i.e., the entire group). Once all particles have been moved, the next iteration starts (Bianchi et al., 2009). PSO is applied in Moghaddas Tafreshi et al. (2016) to solve a non-linear profit maximization problem and in Mao et al. (2010) to solve a MO problem, after transforming it into a SO one by introducing membership degree variable (see Section 5.1). In Huo et al. (2018), a decomposed-PSO algorithm is proposed by combining this method with the interior-point method to solve a non-convex non-linear cost minimization.

Another swarm-intelligence meta-heuristic is the *Artificial Bee Colony* (ABC) algorithms, that mimics the intelligent foraging behavior of honey bees. There are three groups of bees in the colony, which look for the best sources of nectar and share information in order to find the optimal path for the next iteration, until some requirements criteria are met. This algorithm is applied in Safamehr and Rahimi-Kian (2015) to solve a nonlinear optimization problem, both its deterministic and stochastic versions.

The nonlinear minimization cost problem in Rouholamini and Mohammadian (2015) is solved by applying the physical-inspired meta-heuristic *Gravitational Search Algorithm* (GSA). The GSA is based on the law of gravity and mass interaction (Rashedi et al., 2009). The group of potential solutions is represented as a set of objects forming a gravitational systems. The objects interact among each other as masses according to their characteristics, namely position, gravitational mass, and inertia mass. At each iteration of the algorithm, masses are evaluated and their position is determined as the result of attraction forces among each others. System parameters such as the gravitational mass and the gravitational constant are updated accordingly. The procedure is repeated until a stopping criterion is met (Rouholamini and Mohammadian, 2015).

The *Invasive Weed Optimization* (IWO) algorithm used in Lorestani et al. (2016) is a nature-based meta-heuristic, inspired from the growth of weed plants. The algorithm is based on the iteration of three consecutive processes: distribution of seeds, growth of weed plant, and reproduction. The production of seeds depends on the fitness of the weed plant, so that only plants with the best fitness are allowed to spread. The optimized solution is hence represented by the weed plant with the best fitness value (Rad and Lucas, 2007).

Evolutionary Algorithms (EAs) are based on Darwin's theory of natural selection within a population. Starting from an initial population, i.e., a group of potential solutions, crossover and mutation are performed to obtain the offspring population. Solutions are evaluated according to a fitness function, which varies with the defined problem, and a portion of them is selected to generate a new offspring population, by a combination of genetic operators. The procedure is repeated until a termination criteria is met (Marler and Arora, 2004). Among others, *Genetic Algorithm* (GA) have gained popularity in several areas and have been applied to both SO and MO problems. In particular, the non-dominant sorting genetic algorithm (NSGA-II) proposed by Deb et al. (2002) is used in Miyazato et al. (2016) and Braun et al. (2016) to get the Pareto

frontier with trade-offs between two or more objective functions. NSGA-III is the successor to NSGA-II and it is particularly efficient in solving problems in three or higher dimensions, as shown in Braun et al. (2016). A GA-based algorithm is used also in Mauser et al. (2016, 2015) to solve a SO problem. It operates on the global optimization problem that integrates all sub-problems resulting from the dynamic programming approach. In Severini et al. (2013), a GA is used to solve a NLP, describing the thermal dynamics of a household. Two other algorithms used in Braun et al. (2016) to solve a MO problem are SPEA2 (Zitzler et al., 2001) and ESPEA (Braun, 2015). The former belongs to the EAs, while the latter is inspired by the physical phenomenon of electrostatic potential energy.

5.6. Discrete vs. continuous models

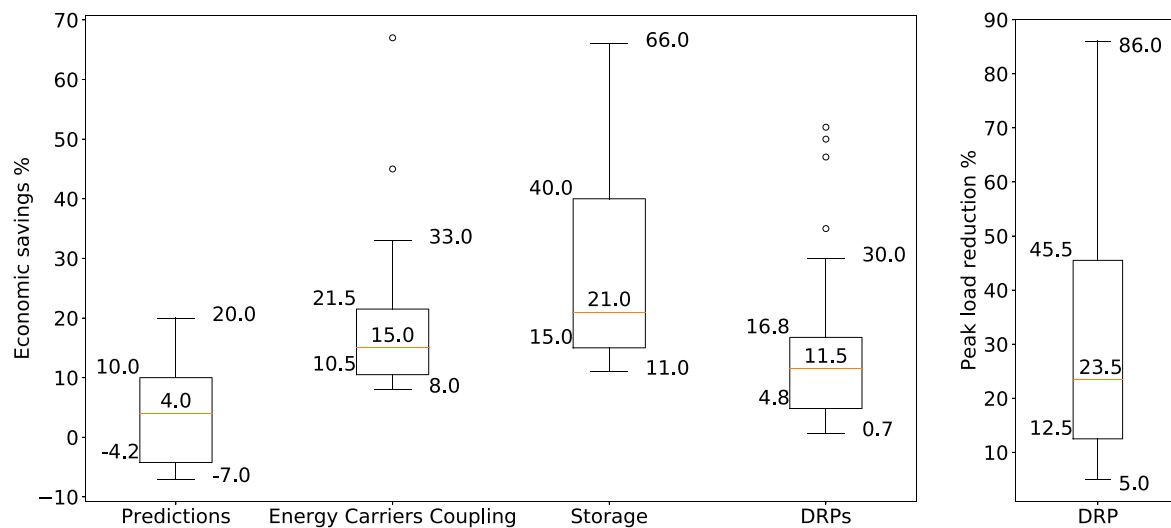
All reviewed studies consider discrete models, that means, state variables change at regularly intervalled, countable points in time. Thus, the system is described by the changing in state at those points in time. It can vary between one minute (e.g., Larsen et al., 2014) and one hour (e.g., Alahäivälä et al., 2015). Alternatively, the number of states is considered infinite, and the system evolves continuously and not abruptly from one state to another. Some studies, e.g., Salpakari and Lund (2016), Shi et al. (2016), propose a continuous formulation of the scheduling problem. Continuous solutions are then discretized for the actual implementation.

6. Potential economic and environmental achievements

The design, implementation, and adoption of energy management systems is a complex process that has to deal with several hurdles, from uncertainty in weather and demand forecasts, to guaranteeing the system's stability, to reducing of the environmental impact. As each of the reviewed studies in this survey proposes its own solution, with multiple variations in terms of size, structure, assumptions, and model, it is not possible, nor fair, to numerically compare the results between studies. Rather we give an impression of the potential economic and environmental achievements due to the optimal resources scheduling.

We define four factors which are found to lead to variation in the energy costs and we classify the achievements of the reviewed papers accordingly. The factors are defined as follows:

- *Predictions*, which includes the use of (almost) real-time data and short-term forecasting approaches, in order to take into account data uncertainties. The savings summarized in Fig. 5a refer to Aki et al. (2016), Holjevac et al. (2015), Kneiske et al. (2018), Severini et al. (2013) and Zhang et al. (2015). Negative values mean that energy costs are increased by considering forecasting of data with uncertainties.
- *Energy Carriers Coupling*, that refers to the development of systems which coordinate multiple energy vectors, usually electricity and hot water, with the aim of supply both power and thermal demand in a flexible way. We include in this group some results from Brandoni et al. (2014), Elkazaz et al. (2016), Farmani et al. (2018), Setlhaolo et al. (2017) and Zhang et al. (2013).
- *Storage*. The introduction of storage devices increases the flexibility of the system in the supply–demand balance. The potential benefits of storage are investigated by Comodi et al. (2015), Dagdougui et al. (2012), Ha et al. (2017), Huo et al. (2018), Lorestani et al. (2016), Parisio et al. (2015), Prinsloo et al. (2016), Salpakari and Lund (2016), Setlhaolo et al. (2017) and Zhang et al. (2015).



(a) Variations in economic savings due to different factors, namely use of prediction models, implementation of DRPs, introduction of storage systems, and coupling of multiple energy carriers. (b) Variations in peak demand reduction due to DRPs.

Fig. 5. Potential economic savings and peak demand reduction. Given a range of possible results, the values shown in the figure represent (from top to bottom) the maximum, third quartile, median, first quartile, and minimum. Circles indicate outliers.

- DRPs, which can involve electric loads, thermal consumptions, electric vehicles, and storage (Alipour et al., 2017; Ashouri et al., 2016; Batić et al., 2016; De Angelis et al., 2013; Kriett and Salani, 2012; Ma et al., 2017; Majidi et al., 2017a,b; Nojavan et al., 2017; Salpakari and Lund, 2016; Setlhaolo et al., 2017; Severini et al., 2013; Sheikhi et al., 2015, 2016; Tabar et al., 2017; Zhang et al., 2013).

The variations in economic savings due to the defined factors are summarized in Fig. 5a, where maximum, third quartile, median, first quartile, and minimum values are shown for each range. When a study presents the simulation of several scenarios and configurations, e.g., with different size of the system (Zhang et al., 2013) or different consumption profiles (Severini et al., 2013), we consider the corresponding results as separate data points.

The median values show that storage devices can have the greatest impact on the economic costs, followed by the coupling of multiple energy carriers, usually by means of (micro)CHP systems. The large majority of studies neglect the investment costs, given their main goal of optimal scheduling, usually in a short time horizon. Therefore, such economic savings may be still insufficient to make the investment profitable, especially in the case of storage (Comodi et al., 2015). The potential effects of DRPs on the energy costs depend on proposed pricing schemes, available technologies, and studied days (hot vs. cold day, weekday vs. weekend, morning vs. evening).

Several studies (Brahman et al., 2015; Perez et al., 2016; Qayyum et al., 2015; Rayati et al., 2015; Safamehr and Rahimi-Kian, 2015; Setlhaolo et al., 2017; Sheikhi et al., 2016; Shirazi and Jadid, 2015; Zhang et al., 2013) estimate the potential of DRPs in lowering the peaks in the demand profile, which is beneficial for the management of the grid. The values in Fig. 5b are quite spread, which is consistent with the evidences from international demand response initiatives (Faruqui and Sergici, 2013).

With respect to environmental achievements, few works include environmental considerations (see Table 8) and even a smaller group quantifies them (Holjevac et al., 2015; Aki et al., 2016; Majidi et al., 2017a,b; Nojavan et al., 2017; Tabar et al., 2017; Skarvelis-Kazakos et al., 2016; Brandoni et al., 2014). Therefore, a graphical representation such as the one we propose for

the economic savings cannot be provided, due to insufficient data points. Further discussions on the potential economic and environmental savings are available in Appendix B.

7. Related works

Other surveys exist in the literature about energy management in energy systems, though the focus is not the same as the survey herewith proposed. Beaudin et al. provide a comparative analysis of the literature on EMS for households, focusing on the modeling approaches and the computational complexity of the scheduling problem (Beaudin and Zareipour, 2015). A chronological overview of the home management models from 1970 until 2014 is proposed in Vega et al. (2015). This paper offers an interesting perspective of the evolution of the models and technologies, from the first applications with integrated infrared sensors till the development of Service-Oriented Architectures and the integration on Smart Meters. The main methods and strategies to develop EMSs in MGs are discussed in Serna-Suárez et al. (2015), although only solutions that may enable generation costs savings are considered. A thorough review of optimization techniques for MGs planning, which includes, among several steps, the resource scheduling as well, is available in Gamarra and Guerrero (2015), whereas energy management strategies for HRESs are surveyed in Olatomiwa et al. (2016). The same techniques may also be applied to design and control DERs (Baños et al., 2011; Theo et al., 2017; Rahman et al., 2015). In Nguyen and Aiello (2013), we propose a survey of energy intelligent buildings, where we investigate which and to what extent user's activities and behaviors impact residential and office building energy consumptions. The available technologies and tools to actually build an EMS, namely sensors, smart meters, communication protocols, and system architectures, are reviewed and compared in De Paola et al. (2014), Kailas et al. (2012) and Amer et al. (2014). A broad survey on the energy savings obtained from applying energy management strategies in 305 actual case studies is proposed in Lee and Cheng (2016), which includes residential, office, commercial, and industrial buildings. An overview of the current status of national programs promoting EMSs and energy audits in European countries shows that only few states have implemented

mandatory or voluntary programs to comply with the European Union's energy efficiency guidelines (Serrenho et al., 2015). To the best of the authors' knowledge, a systematic literature review on operation scheduling of energy resources for residential and office buildings is missing. The present survey attempts to fill this gap by focusing on the optimal scheduling of energy resources to satisfy both end-user's electrical and thermal demand at all level of aggregations, considering methods and techniques to address the multifaceted nature of the energy management problem.

8. Discussion

Next, we discuss how the proposed comparison model has addressed the research questions and the possible limits of our work.

8.1. Outcomes overview

The data extracted from each study (see Section 2.4) have been summarized in several tables for comparison. Tables 2 and 3 compare the approaches taken to formulate the energy management problem, and, in particular, the operation scheduling problem, addressing the first research question: "How to formulate the energy management problem?" The studies are classified according to the problem formulation (i.e., SO or MO), the objective functions to be optimized and their nature. Some studies include environmental goals among their objective functions, while others draw *ex-post* environmental considerations on the energy management problem. Table 8 compares how the environmental aspect is tackled (i.e., within the objective function(s) or *ex-post*) and which source of emissions are taken into account. Table 4 provides an overview of the economic models in terms of power and fuel tariff composition, which is key aspect of the formulation of economic objective functions. RES incentives and emission costs are further discussed in Section 4.3.

As for the second research questions, "Which are the most common system models, such as DERs, loads, and infrastructure?" we look at the system modeling approach. In particular, Table 1 classifies the studies based on the aggregation levels, whose minimum requirements are summarized in Fig. 1. Table 5 illustrates the frequency of appearance of certain DERs in the reviewed papers, whereas Table 6 summarizes the load models. The studies are classified on the basis of the composition of the power profile, of the type of thermal load, and on the level of DRPs load flexibility. As for the infrastructural aspect, Table 7 distinguishes the different approaches in representing the connection to the main distribution grids and among MESs.

The main optimization techniques are summarized in Table 9, where the studies are classified according to the approached used to deal with MO problems, to seek for a (near-) optimal solution, and to deal with information uncertainties. Moreover, a classification of the optimization methods is provided in Fig. 4, addressing the last two research questions, "Which are the most common optimization methods?" and "How to deal with forecast uncertainties?"

8.2. Limitations of this study

Although we have followed the steps presented in Section 2 in a rigorous way, our work may exhibit the following limitations. The preliminary search was conducted on Google Scholar, based on a list of keywords and subject to a restriction on the publishing date, i.e., 2010 or after. This implies that we may have missed some relevant studies which use different keywords or in a different combination, or have been published before 2010. Yet, given that the initial number of retrieved documents amounted

to around 3,790 publications, we are likely to have retrieved the majority of the most recent and significant studies.

Another limitation may come from including only papers that address the supply of both power and thermal demand. A large share of the available literature on energy management systems focuses mainly or exclusively on power demand, therefore, we may have missed some interesting methods and techniques that could be applied to MESs as well. Yet, we believe in the importance of having a complete overview of the energy consumptions, that means, considering systematically the thermal load next to the power load. In fact, space heating and cooling, and hot water demand are often the biggest contributors to energy consumption.

As for the optimization methods, this study offers an overview of the most common techniques, discussing the main concepts and the most significant differences. However, problem complexity and required computational capacity are not addressed, although they may be a key aspect while developing EMS. The interested is referred to, e.g., Schrijver (1986), Floudas and Lin (2005), Beaudin and Zareipour (2015) and Blum and Roli (2003) for more in-depth treatments. Moreover, unlike the present work, the studies could have been classified according to the tools and softwares used to solve the energy management problem, as done in other studies, e.g., Ahmad Khan et al. (2016).

In summarizing the potential economic and environmental achievements (see Section 6), this study considers the methods and the results of all reviewed papers technically valid, although some approaches may be more realistic and/or rigorous than others. In particular, a cost-benefit evaluation of the proposed approaches, e.g., costs due to the integration of storage systems and/or multiple DERs vs. economic savings, could help understanding the feasibility of such potential results. Yet, given the large variety of systems, both in size and complexity, such an evaluation would require the definition of a rigorous economic model and method, that is beyond the scope of the present work.

9. Conclusions

Operation scheduling of DERs and flexible loads in residential and office environments is close to becoming a reality thanks to the many recent studies on the subject. We have reviewed recent literature on the topic. We presented the different aggregation levels used for describing the interconnections among the thermal and electrical loads, generation, transformation, and storage resources. The operation of such frameworks is determined by various objectives, which have a commercial, environmental, social, and/or technical nature. Different approaches are common in describing the information affecting the scheduling, which aim at representing the uncertain nature of weather forecasts, market outputs, user's behavior, and energy demand. According to the modeling choices, several techniques and methods can be employed to find the optimal or near-optimal scheduling. Some provide provably optimal solutions while other aim at founding rapidly good-enough solutions.

We have overviewed many approaches are employed in describing and solving the optimization scheduling problem. Therefore, it is difficult, nor fair to compare the effectiveness of the approaches and the relative results. Nevertheless, we can draw some conclusions that, in turn, suggest how to effectively model and control an EMS for residential and office buildings:

- The majority of studies aim at minimizing the energy costs, although a cost-based scheduling may not lead to the most sustainable solution. Given the environmental impact of the energy sector, ignoring the dual, often counterposed nature of the problem should be avoided.

- Among DERs, (micro)CHPs play a central role in increasing economical and environmental saving and achieving higher self-sufficiency. Such systems show great flexibility in production, given that it is not affected by external and unpredictable factors, while reducing the dependency on the main distribution grid and the volatile electricity market.
- Integrating the use of various energy carriers by means of hybrid loads and appliances allows further savings by taking advantage of the differences between electricity and gas. On the one hand, the variation in electricity prices may enable higher profits. On the other hand, the gas price is known in advance and often lower than electricity. By an environmental point of view, the emissions associated to the combustion of gas are constant, while the electricity carbon intensity strongly depend on the energy mix, which varies in time (e.g., daily and seasonally) and in space (e.g., countries).
- Although perfect information can be useful for simplifying the complexity of the optimal scheduling problem, neglecting the impact of uncertainty may lead to an overestimation of the potential benefits.
- In order to increase the acceptability of automated EMSs, user preferences and, hence, user comfort should always be taken into account.
- Modeling the energy demand in an aggregated way, without distinguish at least between flexible and non-flexible loads, does not allow a further investigation on the real capabilities of participating in DRPs.
- A decentralized approach where only information on the overall power profiles are shared is likely to be more accepted by users, given that detailed information such as user's preferences and usage of single devices would be kept private.

As we discussed in Section 6, the large variety of models and approaches make the comparison and evaluation of results difficult and, to some extent, even of little value. Therefore, as already suggested in Beaudin and Zareipour (2015), we believe that it would be extremely useful to have reference use cases, for instance according to the different type of aggregation levels and buildings, to be used as a baseline for comparison of results. Such use cases should include a minimum set of DERs with standard parameters, standard user's preferences for thermal conditions and load shifting, and datasets with uncertainty for exogenous variables, such as energy prices and RES production. The use of historical data would then be a further demonstration of the capability and potential benefits of the proposed approach within more specific scenarios.

Although the benefits of implementing EMSs for the optimal scheduling of loads and resources are evident, both from the end-users' and energy utilities' point of view, it is extremely important to take into account users' preferences and their openness toward accepting such systems. In fact, the amount of information involved in the scheduling problem is so large that it would be difficult, or even impossible for the average end-user to understand it. At the same time the users have to accept a certain level of automation and consequent loss of control at the risk of a drop in comfort. Users can be encouraged to employ automated EMSs if they have the possibility not only of shifting their energy usage, but also of changing their energy resources, while keeping their overall consumptions unchanged. In this context, MESs are the key approach, where power and thermal loads can be supplied by different and, to a certain extent, interchangeable energy carriers. With the growth in building automation systems and the constantly falling technology costs (Department for Business, Energy & Industrial Strategy, 2018), energy management systems will have a central role in the transition toward smart energy systems, providing flexibility in supply and demand, while enabling cost savings and reducing the environmental impact of energy consumptions.

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Appendix A. Energy management systems and aggregation levels

A.1. Energy management system

The Verein Deutscher Ingenieure (VDI)-Guideline 4602 (VDI, 2007) defines an energy management system as “the proactive, organized and systematic coordination of procurement, conversion, distribution and use of energy to meet the requirements, taking into account environmental and economic objectives”. In other words, an EMS is a decision making tool that determines the operation schedule of dispatchable generation resources and (flexible) loads, by using a scheduling algorithm and information coming from DERs (e.g., forecast and measurement of wind and solar production), energy markets (price signals), and consumers (e.g., forecast and measurement of consumptions and preferences). Different names are used to refer to EMSs (Aki et al., 2016; Prinsloo et al., 2016; Ashouri et al., 2016; Anvari-Moghaddam et al., 2015), such as central controller (Holjevac et al., 2015; Dagdougui et al., 2012), controller (Ashouri et al., 2016; Kneiske et al., 2018), smart controller (Shirazi and Jadid, 2015, 2017), energy management controller (Lorestani et al., 2016), smart decision maker (Brahman et al., 2015), centralized intelligence (Dagdougui et al., 2012), scheduler (Georgievski et al., 2012), planner (Georgievski et al., 2013), composition layer (Kaldeli et al., 2013), optimizer (Shaneb et al., 2012), and energy demand aggregator (Brenna et al., 2015).

A.2. Users

Although the traditional user does not produce electricity, some studies investigate the potential benefits of scheduling controllable loads. In Fiorini and Aiello (2018), we focus on the environmental impact of a single user connected to both the gas and the electricity distribution grid, while 40 households are centrally controlled in Perez et al. (2016).

A.3. Prosumers

The growing amount of small-scale DERs installed at the distribution level is the result of the “prosumerism”, which is boosted by the government incentives, rated energy tariffs, fall in prices for DERs (Van Der Schoor and Scholtens, 2015; Allan et al., 2015), and government incentives (Allan et al., 2015). Some studies (Alahäivälä et al., 2015; Brandoni et al., 2014; Miyazato et al., 2016; Ashouri et al., 2016; Zhao et al., 2013; Lorestani et al., 2016; Mauser et al., 2016, 2015; Razmara et al., 2017; Salpakari and Lund, 2016; Severini et al., 2013; Shirazi and Jadid, 2015; Sheikhi et al., 2016; Shi et al., 2016; Shirazi and Jadid, 2017; De Angelis et al., 2013) consider a single prosumer with several DERs whose schedule has to be optimized. Prosumers may exchange electricity with the main grid (Shaneb et al., 2012; Ashouri et al., 2016; Zhao et al., 2013; Kolen et al., 2017; Jiang et al., 2017; Kneiske et al., 2018; Maurer et al., 2016; Mohsenzadeh and Pang, 2018; Razmara et al., 2017; Salpakari and Lund, 2016; Salpakari et al., 2017; Rodriguez-diaz et al., 2017; Severini et al., 2013; Shirazi and Jadid, 2015; Sheikhi et al., 2016; Zhang

Table 10
Acronyms and abbreviations.

Abbreviation	Description	Abbreviation	Description
ABC	Artificial Bee Colony	LPG	Liquefied Petroleum Gas
AC	Air Conditioning	MA	Multi-Agent
CCHP	Combined Cooling Heat and Power	MES	Multi-Energy System
CHP	Combined Heat and Power	MG	Microgrid
CO ₂	Carbon Dioxide	MILP	Mixed-Integer Linear Programming
DER	Distributed Energy Resource	MINLP	Mixed-Integer Non-Linear Programming
DOE	U.S. Department of Energy	MIP	Mixed-Integer Programming
DP	Dynamic Programming	MIQP	Mixed-Integer Quadratic Programming
DRP	Demand Response Program	MO	Multi-Objective
EA	Evolutionary Algorithm	MPC	Model Predictive Control
EES	Electrochemical Energy Storage	MT	Micro Turbine
EHP	Electric Heat Pump	NLP	Non-Linear Programming
EMS	Energy Management System	PDF	Probability Distribution Function
FC	Fuel Cell	PEV	Plug-in Electric Vehicles
GA	Genetic Algorithm	PSO	Particle Swarm Optimization
GSA	Gravitational Search Algorithm	PV	Photovoltaic
GT	Gas Turbine	QP	Quadratic Programming
HRES	Hybrid Renewable Energy System	RES	Renewable Energy Sources
ICE	Internal Combustion Engine	SO	Single-Objective
IoT	Internet of Things	TES	Thermal Energy Storage
IP	Integer Programming	V2G	Vehicle to Grid
IWO	Invasive Weed Optimization	VPP	Virtual Power Plant
LP	Linear Programming	WT	Wind Turbine

et al., 2013) and among neighbors (Aki et al., 2016; Elkazaz et al., 2016; Larsen et al., 2014). Residential dwellings are interconnected and import/export among themselves locally produced electricity (Larsen et al., 2014) and thermal power (Elkazaz et al., 2016) or hot water (Aki et al., 2016). A large group of buildings connected to the same feeder is referred to as an energy district in Good and Mancarella (2017); similarly, in Mohsenzadeh and Pang (2018) around 700 residential households are connected to a distribution substation, and nodal consumptions and productions are scheduled by a centralized EMS.

A.4. Energy hubs

An energy hub can be described as a “block” that exchanges energy with the neighboring systems via input and output ports. Inputs can be in the form of both primary energy, e.g., natural gas, and secondary energy coming from external grids, such as electricity or district heat. Outputs are usually electricity and heat, locally produced and converted by means of generation and transformation units, such as transformers, CCHP systems, and boilers (Geidl and Andersson, 2007; Mancarella, 2014). Both thermal and electric storage are often included in the energy hub model as well, which is traditionally described by a coupling matrix that determines the outputs given the inputs and generation/conversion/storage units. Several real systems can be modeled as an energy hub, from power plants to buildings and districts (Geidl and Andersson, 2007).

A.5. Hybrid renewable energy system

That of Hybrid Renewable Energy System (HRES) is a broad concept that refers to a group of RES, conventional distributed generation, and storage systems for load demand satisfaction (Fathima and Palanisamy, 2015). The term HRES can indicate a few PV panels or a WT coupled with a battery, as well as a more complex system, as in Nojavan et al. (2017) and Majidi et al. (2017a), where PVs, FCs, a back-up boiler, and both electrical and thermal storages are involved. In Dagdougui et al. (2012), the proposed HRES includes only renewable sources, namely PV modules, a solar collector, a WT, and a biomass unit. Similarly, in Rouholamini and Mohammadian (2015), the system is equipped with a small-scale hydrogen production-storage system, which includes an electrolyzer and a H₂ tank for a FC.

A.6. Microgrids

A MG is defined by the DOE as “a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A MG can connect and disconnect from the grid to enable it to operate in both grid-connected or islanded-mode” (Ton and Smith, 2012). The concept of MG can be extended to include not only electricity, but also thermal power. For instance, the work in Holjevac et al. (2015) presents a simulation of both on-line and off-line operation of a MG and evaluate its flexibility in reducing operational costs and emission, while supplying flexible electrical and thermal demands. Similarly, several works manage CHP-based MGs by finding the optimal set point of DERs and by applying DR programs to reshape the load profile (e.g., Alipour et al., 2015; Safamehr and Rahimi-Kian, 2015; Kriett and Salani, 2012; Anvari-Moghaddam et al., 2015, 2017; Mahoor et al., 2013; Mohammadi et al., 2017; Rodriguez-diaz et al., 2017; Zhang et al., 2015). It is important to underline that some of the reviewed studies on MGs actually do not investigate the possibility of islanding operation, while keeping the characteristic of being a cluster of DERs seen by the main grid as a single entity (Tabar et al., 2017; Kriett and Salani, 2012; Anvari-Moghaddam et al., 2017; Comodi et al., 2015; Farmani et al., 2018; Huber et al., 2013; Moghaddas Tafreshi et al., 2016; Parisio et al., 2015, 2017; Rodriguez-diaz et al., 2017; Salpakari et al., 2017; Zhang et al., 2015).

A.7. Virtual power plants

A VPP is defined by the FENIX project (FENIX project, 2007) as an entity that “aggregates the capacity of many diverse DERs, it creates a single operating profile from a composite of the parameters characterizing each DERs and can incorporate the impact of the network on aggregate DERs output. A VPP is a flexible representation of a portfolio of DERs that can be used to make contract in the wholesale market and to offer services to the system operators”. The concept of VPP has been traditionally used in the industrial sector, giving small power plants owners the possibility to “collectively” access and trade on the energy market (Giuntoli and Poli, 2013). However, the concept can be extended to residential users, as they can offer flexibility in return for profit. In Brenna et al. (2015), the VPP model is used to describe residential and tertiary

users, which are referred to as Sustainable Energy Microsystem and include electric mobility, electric vehicles, small-scale RES plants, CCHP generators, and the heating and cooling system. In Skarvelis-Kazakos et al. (2016), different aggregation levels are considered within a hierarchical structure. A group of DERs and 20 residential loads are represented as an energy hub, with input and output ports. The interaction between the hub and the distribution grids is modeled as a microgrid, whereas the trades with the energy markets are defined by a VPP.

A.8. Smart grid

“Smart Grid” is the broadest concept that encompasses all previously defined levels and refers to the new vision of the electricity grid, from transmission to distribution. The main goal is to build on the available infrastructure to increase the efficiency and reliability of the system, the security of supply, the use of renewable sources, and the operational flexibility and sustainability exploiting the increasing availability of information and communication technologies (Gharavi and Ghafurian, 2011). The key element to achieve such an electric grid is a secure exchange of information to promote the coordination and interoperability among all energy stakeholders: from energy utilities, to buildings, to smart appliances.

Appendix B. Economic and environmental savings

Traditional energy systems are managed such that the supply of energy follows the demand, having a (limited) flexibility on the generation side, provided by spinning reserve and balancing power of centralized plants. In this scenario, any generation or consumption mismatch has to be compensated by other generating units, either already running or that can be rapidly turned on or off. Such balancing service has to be remunerated and its costs affect the total cost of the power system, up to 5% (Hirth and Ziegenhagen, 2015).

The use of (almost) real-time data at the distribution level can have a significant impact on both economic and environmental costs, making the system more flexible and ready to balance RES and load uncertainties, reducing the import of power from the main grid and improving the overall efficiency. In particular, it is estimated that by using short-term predictions of the thermal demand and RES production, 2% to 6% of daily energy costs and emissions of a MG can be saved (Zhang et al., 2015; Holjevac et al., 2015), compared to a fully known scenario. When including also the power demand, energy costs and emissions can be reduced by 10%–20% and by 5%–10%, respectively, compared to simulations without demand prediction (Aki et al., 2016). According to Moghaddas Tafreshi et al. (2016), Severini et al. (2013) and Kneiske et al. (2018), ignoring uncertainties of energy systems such as load and RES forecasts could misrepresent their real world operation and economic aspects, overestimating the potential system savings by 0.1% to 7%.

The development of hybrid systems is encouraged by looking at the energy demand as a whole, including both power and heat, which are supplied by multiple energy carriers, usually electricity and hot water. In this context, CHPs play a central role, with the possibility of simultaneously producing electricity and heat, by burning natural gas or other fuels. The coordinated operation of multiple energy carriers decrease the overall operation costs and improve the energy efficiency of the system (Ma et al., 2017), taking advantage of the dispatchable nature of fossil-fired components, unless the costs for the infrastructure and distribution of fossil fuels are not affordable (Lorestani et al., 2016). In a traditional scenario, a boiler usually supplies the thermal load, while the grid supplies the electricity for the power demand, as well

as the cooling one by means of a compression chiller. Assuming such scenario as a reference, Brandoni et al. show that a microCHP can yield up to 12% and 6% of energy savings in a residential 10-flat apartment building and in an office, respectively (Brandoni et al., 2014). At the same time, energy bills could be cut by 8% and 9%, respectively. Further improvements can be achieved by employing a hybrid microCCHP and a solar unit, reaching 29% and 33% energy saving, and 45% and 67% cost saving in the residential building and the office, respectively. Compared to a traditional scenario without coupling of different energy carriers, a MG with 20 to 90 households can reduce daily energy costs by 6% (Skarvelis-Kazakos et al., 2016) to 17% (Zhang et al., 2013), and, similarly, by 15% for a 10-apartment building (Farmani et al., 2018). More promising economic savings of around 30%–35%, are estimated for a 750-customer community in Sheikhhi et al. (2015) and for a four-houses system in Elkazaz et al. (2016), while a CHP can enable up to 23% cost savings in a single smart home (Setlhaolo et al., 2017). Moreover, a microCHP-based system can take advantage of low electricity price hours and deal with electricity surplus by including a resistor into the heating system, increasing the economic savings by 1.5% (Alahäivälä et al., 2015).

Other key elements for the coupling of electricity and natural gas are the storage devices. A TES stores heat produced by gas, but also electricity heat, for instance via an electric resistance. Similarly, a battery can be charged by the electricity generated by a gas-burning CHP as a by-product. The optimal size of both electrical and thermal storage devices is a critical aspect of the energy management problem as, on the one hand, an under-sized device can limit the potential benefits, but on the other hand, an over-sized one can cause great losses (Alahäivälä et al., 2015). The effects of battery's capacity in terms of electricity bill and costs reduction due to load regulation are discussed in Miyazato et al. (2016). The study shows somehow intuitively that a large battery capacity reduces electricity bills, as more energy can be stored during low price hours, and, at the same time, minimizes the required load regulation. However, technological limits and current investment costs can represent an obstacle to the employment of devices with larger capacity (Comodi et al., 2015). In particular, battery degradation costs can penalize the operation costs of the overall system by around 1% (Javadi et al., 2017; Huo et al., 2018), making it necessary to limit the discharging to 60%–90% of storage capacity (Huo et al., 2018) and, hence, the potential savings. According to Salpakari et al. (2017), neglecting the battery degradation can lead to overestimate the cost–benefit of vehicle to grid (V2G) technologies up to 5%, especially when new batteries are considered and their degradation is faster. As for the storage efficiency, the results in Lorestani et al. (2016) indicate that electricity prices influence the lowest efficiency of battery that allows it to cooperate in shifting energy over time and reducing the energy bills. If the storage efficiency is lower than the threshold, the battery will fully discharge in the first interval of peak price and its operation will not be economically convenient. Nevertheless, the potential benefits enabled by the use of storage are indisputable. In a favorable solar day conditions, using solar panels coupled with a storage system can reduce the daily energy costs of an energy hub supplying residential loads by around –15% (Ha et al., 2017; Huo et al., 2018; Setlhaolo et al., 2017), and up to 25% for four smart homes (Lorestani et al., 2016). For residential MGs, a storage is estimated to allow 3%–6% (Kriett and Salani, 2012), 11% (Parisio et al., 2015) and 23% (Zhang et al., 2015) of cost savings. Introducing an optimal-sized storage can reduce the energy costs of a residential building by 19% (Salpakari and Lund, 2016) to 54% (Dagdougui et al., 2012) and for a MG by –66% (Prinsloo et al., 2016). In particular, the integration of electrical and thermal storage with the possibility of using the electricity surplus to produce hot water and supply

the heat pump can halve the electricity bought from the grid and reduce by energy costs by up to 45% with respect to a scenario without storage devices (Comodi et al., 2015), improving the self-sufficiency and efficiency of a hybrid system.

The analysis presented in Huber et al. (2013) offers interesting conclusions on the potential benefits of coordinating a group of loads and generation units. The authors show that the use of PV panels and CHPs increase system autonomy from the main distribution grid when prosumers are interconnected, so that they can exchange energy among themselves. By doing so, the energy autonomy can vary between 38%, when PV panels are installed, and 64% with CHPs, considering in both cases that homes are connected, but not centrally coordinated. A further increase on autonomy is reached with an EMS that can control all generation units, reaching 45% with PV panels and up to almost 100% with CHPs and PV panels. Beyond the numerical results, the study gives valuable insights on the importance of interconnection and coordination among different entities in order to enhance potential benefits and make costly solutions more profitable.

Together with self-generation and storage of energy, changing the consumption patterns according to DRPs has a great economic and environmental impact, while increasing the flexibility of the overall system in the supply–demand balance (Ma et al., 2017). The quantification of the savings significantly varies among the reviewed studies. According to the lowest estimates (Majidi et al., 2017b; Nojavan et al., 2017; Majidi et al., 2017a), applying DRPs reduces operation costs and total emissions by 0.69–3.1% and 0.54–0.84%, respectively. Meanwhile, other studies are more encouraging reaching cost savings up to 7% (Ma et al., 2017), 11% (Tabar et al., 2017) or 20% (Sheikhi et al., 2016; Zhang et al., 2013) and emission reduction up to 1.5% (Tabar et al., 2017). When DRPs are applied to both thermal and power demands, with the former being curtailable and/or shiftable within a certain temperature bandwidth, system costs can be reduced from 6% (Alipour et al., 2017; Kriett and Salani, 2012) to 10% (Batić et al., 2016), and up to 15% (Ashouri et al., 2016; Salpakari et al., 2017). According to Sethaolo et al. (2017), flexible appliances alone can reduce energy costs by 47%, and up to 70% when a PV/battery systems and a CHP are used as well. Compared to a non-optimized energy management, the optimal scheduling of residential electric appliances, thermal load, and storage enables between 30% and 65% cost savings within different dynamic price schemes (De Angelis et al., 2013; Severini et al., 2013). DRPs can be further extended to include the management of smart electric vehicles, which act as active loads that are charged during off-peak hours and sell the stored energy at a later high-price time. In this case, the daily savings in energy costs reach up to 20%, compared to a traditional case without DRPs, and even up to 43%, when also smart management of thermal storage and V2G devices are included. On a yearly basis, V2G technology and smart control of space heating achieve up to 20% cost savings for a single household, and up to 33% for a group of 1–10 households, which cooperate and exchange electricity. According to Qayyum et al. (2015), a residential time-of-use-based DRP involving smart appliances, electric vehicle, and AC system can enable a negative net cost of energy when combined with the export of electricity locally produced by a PV panel. Flexible appliances can also promote self-consumption, decreasing grid feed-in by up to 11% (Salpakari and Lund, 2016), which can be advantageous when feed-in prices are significantly lower than market prices. Encouraging results are achieved also in terms of emissions by reducing the import of electricity and promote the use of natural gas in a CHP system, whose emission factor is usually lower than the one of the reference grid, e.g., 2.5 (Skarvelis-Kazakos et al., 2016) to 4.5 (Brahman et al., 2015) times lower. When the EMS aims at minimizing the emissions, pollution can be

reduced by up to 45%, but the revenues from energy arbitrage (i.e., purchasing and storing energy during off-peak prices periods, and then selling it when prices are the highest) would be limited by the lower import of electricity (Brahman et al., 2015). Emissions minimization can be considered a separate goal from the economic one (Skarvelis-Kazakos et al., 2016), and, to some extent, also counterpose (Brahman et al., 2015). According to Skarvelis-Kazakos et al. (2016), coupling the use of electricity and gas in a 20-household MG allows up to 14% emission reduction. Furthermore, the use of low-carbon technologies can be promoted by incentive schemes, such as feed-in tariffs and carbon tax (Shaneb et al., 2012). In particular, using an EMS to coordinate the operation of a microCHP-based system can achieve up to 24% annual costs saving when a carbon tax of 570 €/tonCO₂ is applied (Shaneb et al., 2012).

The potentials of DRPs can be further enhanced by installing hybrid appliances (Mauser et al., 2016, 2015) or considering hybrid loads (Neyestani et al., 2015), whose required energy can be produced from different energy carriers. The energy efficiency and the flexibility of MESs would be significantly increased. Smart residential building equipped with deferrable hybrid appliances and PV panels can reach up to 60% of self-sufficiency, which is further improved up to almost 100% by introducing a battery (Mauser et al., 2016, 2015). Such appliances not only can be shifted in time, but they also take advantage of the different costs and emissions tied to multiple energy carriers, reducing the economic (Mauser et al., 2016, 2015) and environmental costs (Fiorini and Aiello, 2018) of energy consumptions. Although using electricity for satisfying both the power and thermal demand is usually the most energy-efficient solution thanks to low losses, natural gas is, in fact, often cheaper (Mauser et al., 2016, 2015; Neyestani et al., 2015) as well as lower in carbon emission (Fiorini and Aiello, 2018) than electricity.

The benefits of DRPs are not limited to the user's side. Employing the demand response capability of consumers can significantly reduce the operating costs of the transmission and distribution energy systems. For instance, preventing peaks in the demand promotes a more efficient use of the infrastructure, avoiding bottlenecks, and postponing investments in capacity expansion. In Safamehr and Rahimi-Kian (2015), reduction of 11% peak demand is achieved by shifting flexible demand, estimated at 10% of the total consumptions. Thanks to a centralized control of thermal loads and smart appliances, the peak load demand is reduced by approximately 30% when considering around 750 residential (Sheikhi et al., 2015), by 5%–25% (Perez et al., 2016) up to 89% (Zhang et al., 2013) for a community with 30 to 90 households, and between 6% and 25% (Qayyum et al., 2015; Sheikhi et al., 2016; Shirazi and Jadid, 2015; Brahman et al., 2015) for a single household. The work presented in Rayati et al. (2015) and Setlhaolo et al. (2017) shows that by controlling household loads and generation DERs, the peak load are reduced by 17% and up to 70%, respectively, while energy costs and emission costs are decreased by 40%–70% and 50%–80% respectively. In Mohsenzadeh and Pang (2018), the impact of a nodal-price-based DRP on grid power losses and distribution transformers management is investigated. While the proposed DRP enables the consumer to save around 5 euro per day, when compared to a classical time-of-use DRP; the utility reduces the total energy loss of the grid by 400 kWh a day, and a better management of the demand contributes to increase the lifetime expectation of low voltage distribution transformer. Additionally, DRPs can increase the system's hosting capacity of renewables, avoiding expensive rescheduling procedures of thermal power plants. Assuming that electricity prices decrease with higher share of wind power, users involved in price-based DRPs may be motivated to increase the quantity of power purchased from the utility company and reduce

the use of gas for self production. As a result, a win-win situation is achieved. Consumers' energy costs could decrease up to -12% , wind curtailment would be reduced of up to -80% , and the operating costs of the transmission system would drop by 10% (Jiang et al., 2017). Combining a building EMS with a distribution grid controller can enable up to 42% electricity cost savings, while reducing the fast load variation up to -70% , helping the distribution grid operation (Razmara et al., 2017).

One possible obstacle to the acceptance of DRPs by users may be a perceived or actual drop in comfort, as appliances are automatically scheduled. This issue can be addressed by giving an economic value to user's discomfort (Anvari-Moghaddam et al., 2015; Kriett and Salani, 2012; Rayati et al., 2015). The discomfort can be related to the electric load, when loads are scheduled and run outside a certain desirable time window set by the user (Anvari-Moghaddam et al., 2015; Rayati et al., 2015), and to the PEVs if they are not enough charged when the users need them (Rayati et al., 2015). The user's dissatisfaction is also related to the thermal load, when the difference between the indoor temperature and the set point is greater than a range of a couple of degrees (Kriett and Salani, 2012; Anvari-Moghaddam et al., 2015). The studies show that a smart EMS can reduce the energy costs while guaranteeing a certain level of comfort. In particular, considering a real-time price scheme and a time-of-use one, the smart EMS in Anvari-Moghaddam et al. (2015) reduces the total operation costs by up to 54% and to 47% , respectively, compared to the use of a purely price-based EMS that does not take user's preferences into account. Constant preferred temperatures for hot water and indoor temperature are shown in Shirazi and Jadid (2015) to increase energy costs by up to 27% when compared to a scenario with a range of values. In particular, energy costs increase by 0.1% – 1.8% when constant preferred temperatures increase by $1\text{ }^{\circ}\text{C}$ (Shirazi and Jadid, 2015).

Appendix C. Acronyms and abbreviations

All acronyms and abbreviations are summarized in Table 10.

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